TAMPERE UNIVERSITY OF TECHNOLOGY

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LIQUIDITY EFFECTS OF EARNINGS ANNOUNCEMENTS IN STOCK MARKETS

Master of Science Thesis

Examiner: prof. Juho Kanniainen
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ABSTRACT

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The objective of this study was to find out how the liquidity of a stock limit order book evolves around earnings announcements. The study also addressed the question of how traders behave around earnings announcements. Third aim was to shed light on what are the effects of earnings announcements on information asymmetries.

Liquidity has been recognized as an important factor in the stock markets. However, the shift from dealer markets to limit order markets has changed the liquidity supply: in dealer markets the liquidity is supplied by a market maker and traders only take liquidity, whereas in limit order markets the traders themselves may choose whether to supply or take liquidity. Hence, by studying the liquidity in a limit order market it may be possible to provide information on behaviour of traders and information asymmetries between the traders affecting their trading behaviour. This study used high frequency limit order book data of 75 liquid stocks traded in exchanges belonging to NASDAQ OMX Nordic and earnings announcements released between 2006-2009. The liquidity measure used represents the overall liquidity of a limit order book. The liquidity was studied during 40 minute time window around the releases and compared to the average liquidity during 27 previous trading days.

The study found that the liquidity for large trades is at rather low level before the earnings announcements and the announcements are immediately followed by a peak in illiquidity. However, 20 minutes after the announcements the liquidity for large trades has returned to a normal level. In contrast to this, the liquidity for small trades was found to be at rather normal level before the announcement, but after the announcement it remained at higher level. Based on earlier literature, it was proposed that institutional investors supply liquidity before the announcements while many individual investors have canceled their limit orders, and the peak in illiquidity was interpreted to be due to institutional investors changing the behaviour from supplying liquidity to taking it by executing against individuals' stale limit orders. The peak in illiquidity after the announcement indicated that earnings announcements are followed by momentary increase in information asymmetry. But as the overall liquidity returned to the normal level in 20 minutes after the announcement, using this time period the announcements did seem to decrease information asymmetries.

TIIVISTELMÄ

TAMPEREEN TEKNILLINEN YLIOPISTO
Tuotantotalouden koulutusohjelma
SALO MILLA: Osavuosikatsausten vaikutukset likviditeettiin osakemarkkinoilla
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Tutkimuksen tavoite oli selvittää, miten osakkeen tarjouskirjan likviditeetti kehittyy osavuosikatsausten ympärillä. Tutkimus valaisi myös kysymystä miten sijoittajat käyttäytyvät osavuosikatsausten ympärillä. Kolmas tavoite oli selvittää, miten osavuosikatsaukset vaikuttavat informaation asymmetriaan.

Likviditeetti on tunnistettu tärkeäksi tekijäksi osakemarkkinoilla. Siirtyminen tarjousvetoisiin markkinoihin on kuitenkin muuttanut likviditeetin tarjoamista: perinteisillä markkinoilla markkinatakaaja tarjoaa likviditeettiä ja sijoittajat ottavat sitä, kun taas tarjousvetoisilla markkinoilla sijoittajat voivat itse valita tarjoavatko vai ottavatko he likviditeettiä. Siten tutkimalla likviditeettiä tarjousvetoisilla markkinoilla on mahdollista saada tietoa sijoittajien käyttäytymisestä sekä sijoittajien välisistä informaation asymmetrioista, jotka vaikuttava heidän käyttäytymiseensä. Tässä tutkimuksessa käytettiin tiheänäytteistä dataa 75 likvidistä OMX Nordiciin kuuluvissa pörsseissä listatusta osakkeesta sekä 2006-2009 välisenä aikana julkaistuja osavuosikatsauksia. Käytetty likviditeettimittari mittaa kokonaislikviditeettiä. Likviditeettiä tutkittiin 40 minuutin jaksoissa osavuosikatsausten julkistusten ympärillä, ja tuloksia verrattiin keskimääräiseen likviditeettiin 27 edeltävän päivän aikana.

Tutkimuksessa havaittiin, että likviditeetti suurille kaupoille oli melko alhaisella tasolla ennen osavuosikatsauksia ja niitä seurasi välitön negatiivinen likviditeettishokki. 20 minuuttia julkistuksen jälkeen suurten kauppojen likviditeetti oli kuitenkin palautunut normaalille tasolle. Sen sijaan pienten kauppojen likviditeetin havaittiin olleen lähes normaalilla tasolla ennen julkaisuja, mutta jäävän sen jälkeen matalammalle tasolle. Aiemman kirjallisuuden perusteella ehdotettiin, että institutionaaliset sijoittajat tarjoavat likviditeettiä ennen osavuosikatsauksia yksityisten sijoittajien peruuttaessa aiemmin jättämiään tarjouksia, ja että havaittu likviditeettishokki johtuisi institutionaalisten sijoittajien muutoksesta ottaa likviditeettiä sen tarjoamisen sijaan toteuttamalla kauppoja yksityisten vanhentuneita tarjouksia vastaan. Välitön likviditeettishokki antoi viitteitä siitä, että osavuosikatsauksia seuraa hetkellinen informaation asymmetrian kasvu. Toisaalta koska kokonaislikviditeetti palasi normaalille tasolle 20 minuuttia julkaisun jälkeen, tällä aikavälillä voidaan katsoa, että osavuosikatsaus vähentää informaation asymmetriaa.

PREFACE

It has been kind of a long journey writing this thesis, or at least it has felt long. Nevertheless, it has been really interesting and also rewarding. I have learnt a lot, and the process of doing the research for this thesis will serve as a good starting point for further research.

First of all, I would like to thank my thesis supervisor Juho Kanniainen for all the support and encouragement and for guiding me through this process. I would also like to thank Jaakko Valli for all the valuable discussions and technical support that I got. Furthermore, I wish to thank Ye Yue for all the help in designing the proper statistical tests for the purposes of this research. I would also like to thank my father for having the patience to review my text. In addition, I want to thank my colleagues in the CITER room for all the support that I got with small technical issues as well as for all the mental support. Last but not least, I want to thank Ville for all the mental support that I got and also my dear family for all the valuable support.

Milla Salo

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CONTENTS

LIST OF SYMBOLS AND TERMS

β	overall liquidity measure used in this study, defined in Chapter 6.3. Measures the liquidity (cost of trading) for large trades
κ, proportional spread	spread divided by the mid-price of the corresponding moment
m	log-return on mid-price
$\bar{s}$, mid-price	mid-point of the best ask and bid prices
ask	a sell limit order
bid	a buy limit order
limit order	a commitment to buy or sell a certain amount of a specific stock with predetermined price
limit order book	contains all the limit orders of a specific stock that have been submitted but not executed or canceled
spread	difference between the best ask and bid prices. Measures the liquidity (cost of trading) for small trades

1. INTRODUCTION

Liquidity is an important feature of any well functioning stock market and liquid markets benefit most of the traders (Harris 2002). Since liquidity represents the cost of trading (Amihud and Mendelson 1991), it should be of interest of all traders. The shift to electronic limit order markets from the more traditional dealer markets has changed the nature of liquidity supply: in dealer markets the liquidity is supplied by a specified market maker and traders only take liquidity, whereas in limit order markets the traders themselves may choose whether they want to supply or take liquidity (Foucault et al. 2005). Hence, studying the liquidity in limit order markets is interesting and may also provide information on behaviour of traders and information asymmetries between the traders that affect their trading behaviour.

The objective of this study is to find out how the liquidity of a stock limit order book evolves around earnings announcements. This is done by studying the limit order book of 75 stocks traded in OMX Helsinki, OMX Stockholm and OMX Copenhagen around earnings announcement releases during the years from 2006 to 2009. Stocks in the sample are restricted to frequently traded and liquid stocks. Another question this study aims to shed light on is how traders behave around earnings announcements and what are the effects of earnings announcements on information asymmetries in the market. The second question is addressed based on the results concerning the liquidity and earlier research. In contrast to many earlier researches on related subjects, this study uses high frequency data. In addition, the liquidity measure used in this study aims to measure the overall liquidity of a limit order book and thus takes into account also price levels beyond the best ask and bid prices.

This thesis is constructed as follows. Chapter 2 begins by explaining the basic concepts of limit order book and market architecture. Then Chapters 3 and 4 will go on to the liquidity and asymmetric information explaining the terms and reviewing related literature. Next, in the Chapter 5, market architecture of the markets studied is presented. Chapter 6 describes the data used in this study, demonstrates the liquidity measure used and goes through some of the characteristics of the order book data. Then Chapter 7 will proceed to explain the methods used to study the limit order book and illustrate the results. Chapter 8 discusses the findings of

Chapter 7 and briefly assesses the success and limitations of this study. Finally, Chapter 9 concludes by giving a short summary.

2. LIMIT ORDER MARKETS

2.1 Basics of limit order book

Nowadays most of the modern stock exchanges in the world are limit order based electronic markets. In limit order markets the market participants can submit limit orders, which means that they commit to buy (a buy limit order, bid) or sell (a sell limit order, ask) a certain amount of stocks with a predetermined price. The submitted order is valid until it gets executed or canceled. A buy (sell) limit order execution takes place when an other market participant submits a sell (buy) market order or a marketable sell (buy) limit order. (Parlour and Seppi 2008) Marketable sell limit order is a sell limit order with a price at or below the best (highest) bid price and respectively marketable buy limit order has a price equal or higher than the best (lowest) ask price, and hence gets executed immediately (Anand et al. 2005). A market order on the other hand gets executed immediately when submitted at the best price currently available (Parlour and Seppi 2008). So the limit orders can be seen as guaranteeing the price but not the execution, whereas market orders guarantee the execution but not the price (O'hara 1995, p. 191).

Limit order book contains all the limit orders of a specific stock that have been submitted but not executed or canceled. Figure 1 illustrates a limit order book for a specific stock at a specific moment. To be precise, Figure 1 does not show the whole order book, but twenty best ask and bid price levels, so it is possible that more price levels and so submitted limit orders exist at that moment, but they have worse price and hence are not shown in the figure. Negative order quantity refers to buy limit orders and positive to sell limit orders, as done also by Malo and Pennanen (2012).

Figure 1 helps to illustrate the discriminatory pricing in limit order markets. Discriminatory pricing denotes that rather than having uniform prices, market orders walk up the book (Biais et al. 2005). This means for example in the case of Figure 1, that when a market participant submits a market order to buy 2×10^5 shares, one has to pay 15.59 Euro for the first ones, 15.60 Euro for the second ones and so on until the desired quantity is reached. So the buyer does not pay the same price for all the shares but has to clime up the prices in the book to be able to buy more

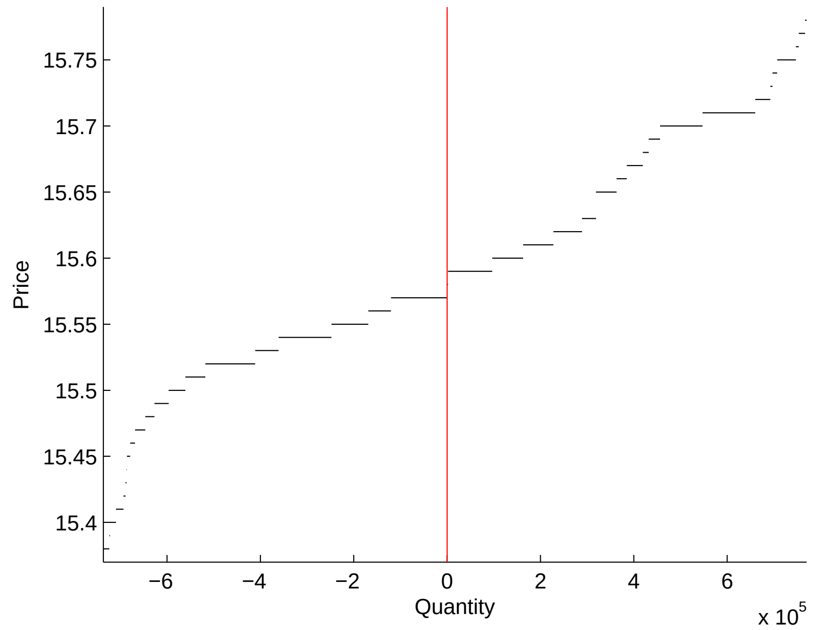

Figure 1: The limit order book of Nokia 3.1.2006 at 15:59:30 with twenty best bid and ask prices. The left side of the red line at zero quantity contains the bids and is referred as the bid side of the book and the right side contains the asks and is referred as the ask side of the book.

shares than are available at the best ask price.

Price and time priority rules usually direct the execution of limit orders. The price priority simply means that the limit orders with best bid and ask prices get executed first. The time priority on the other hand refers to the order in which the limit orders with the same price get executed: oldest limit orders get executed first. (Parlour and Seppi 2008) Limit orders can also be seen as "free options", since submitting a limit order is in effect equal to giving a free option. As the value of the stock changes, it is possible that the limit order gets "picked off" at worse price than the value of the stock at that moment. This risk can be reduced by continuously monitoring the market, but this of course raises monitoring costs. (O'hara 1995)

An important concept related to a limit order book is spread. It is defined to be the difference between the best ask and bid prices (Harris 2002). The depth of an order book on the other hand refers to the outstanding limit orders in the limit order book (Cont et al. 2011).

Cao et al. (2009) argue that traders get a picture of the demand and supply in the market by looking at the shape of the book, i.e. how many shares there are at each level and what is the distance between the levels. Asymmetries between the sides of the book can indicate shifts in the demand and supply curves that are caused by some unobservable factors that affect the price of the share. When observing the supply and demand, traders have better chance to guess these factors and hence predict the movements of the price in the future. (Cao et al. 2009)

Hedvall et al. (1997) study the symmetry of market order submissions in a limit order market[1]. The findings suggest that the flow of market orders is rather symmetric. The frequency of a buy market order followed by another buy market order is the same as the frequency of a sell market order followed by a sell market order, and the frequency of a buy market order followed by a sell market is the same as for a sell market order followed by a buy market order. (Hedvall et al. 1997)

2.2 Market architecture

To be able to understand the impact of market structure on the results of researches published earlier that are introduced in later the chapters, and, on the other hand, to be able to evaluate the applicability of those results in the context of this study, we now go through the basic characteristics that can differentiate stock markets from each other. Madhavan (2000) uses the term market architecture about these rules that control the trading process. The concept of market architecture described here is used when introducing the markets studied in this study in Chapter 5.

According to Madhavan (2000), the market type is determined by three aspects: degree of continuity, reliance on market makers and degree of automation. In continues markets the trading is allowed continuously, i.e. while the market is open, all market participants can trade at any point in time. The opposite of continuous trading system is periodic system, which allows trading only at specific points in time. Reliance on market makers refers to if the market has a market maker, also referred as specialist, with whom the other market participants must trade. In markets with market maker, also called quote-driven markets, the market maker is always the other side in every trade. Instead in markets without a market maker, usually referred as order-driven markets, market participants trade with each other without a market maker intermediation. It is also possible to have an order-driven market with a market maker providing liquidity in exchange for some privileges, in which case it is not necessary so that the market maker is the other side of every trade. A market may also have more than one competing market makers. The third aspect determining the market type, degree of automation, concerns if the orders

[1] In fact Hedvall et al. (1997) study a limit order market where only limit orders are allowed, but since they study the submissions of limit orders that get executed immediately, in effect in the context of this study they are studying market orders.

are submitted face to face in a specific place, "on floor", or in electronic systems. The automation of the systems is not considered to be as important as the rules that actually instruct the trading. (Madhavan 2000)

Price discovery is also one definer of markets. It specifies to what extend independent price discovery is possible or is the price used in the market determined in another market. Also permitted order forms affect the market. (Madhavan 2000) We have already introduced two simple examples of order forms, namely limit order and market order. Some other order forms are introduced in Chapter 2.1 where the architecture of the markets studied in this research are discussed in detail. Limit orders form naturally an important part of pure order-driven markets, but nowadays they play an increasingly important role also in dealer markets such as New York Stock Exchange (NYSE)[2] (Ahn et al. 2001). Protocols used in the market affect the trading too, for example the minimum tick[3] used and special rules used during opening the market and to halt trading (Madhavan 2000).

The last determinator of markets mentioned by Madhavan (2000) is transparency. It means what kind of information the traders get during the trading process, e.g. to what extent the market participants can observe the trades made by other market participants or limit orders submitted but not executed. (Madhavan 2000) For example it is possible that market participants only see the best bid and ask prices, or also the quantities offered or, in highly transparent markets, they can see all prices and quantities of orders submitted. When all limit orders are observable to all traders, it is called the open book and if the traders cannot see the book it is called closed. The transparency can also concern the information about the identity of traders. (Parlour and Seppi 2008)

Some basic examples of different ways of organizing the markets are call auctions, dealer markets, and limit order markets (Foucault et al. 2005). The trading in call auctions is periodic, i.e. the degree of continuity is low (Madhavan 2000). Since the trading takes place only at specified moments, immediate execution is possible only by chance (Foucault et al. 2005). In dealer markets there exist a market maker which may take the opposite side of every trade and determines the bid and ask quotes (Madhavan 2000). Dealer markets are continuous, so one can trade at any moment preferred, but the cost of immediacy can affect the prices compared to call auctions (Foucault et al. 2005), because the market maker has to keep inventory and the market maker faces adverse selection problem discussed

[2] The market maker is called specialist in NYSE and hence it can also be referred as a specialist market.

[3] Minimum tick is the minimum difference between two prices (NASDAQ OMX Nordic 2011).

in section 4.1, and hence needs to be compensated for those (O'hara 1995). In the limit order markets, on the other hand, the traders can demand immediacy by submitting a market order and pay a higher price than when entering a limit order and thus supplying immediacy and getting later (not certain) execution at more desirable price (Foucault et al. 2005). Typically limit order markets are relatively transparent compared to dealer markets. Dealer markets usually only disseminate the best quotes of the market maker, whereas in limit order market the traders can often see a number of price levels with quantities, and these are usually immediately available for execution. In dealer markets prices for trades exceeding the quantities offered (by the market maker) at the quotes must be negotiated with the market maker. (Cao et al. 2009)

3. LIQUIDITY

3.1 Defining liquidity

According to O'hara (1995, p. 216), liquidity has long been seen as an important factor of market behaviour. Harris (2002) contributes that liquidity is the most important feature of markets that function well. Nevertheless, liquidity is not as well defined as one would assume, since it can mean different things to different people (Harris 2002). While maybe easy to recognize, apparently liquidity is not that easy to define[1] (Irvine et al. 2000, O'hara 1995, p. 215).

The difficulty of defining the liquidity lies in the many dimensions of liquidity. Liquidity can be seen as ability to trade quickly, i.e. being able to buy or sell at desired moment without having to wait. Other aspect is to be able to trade also large quantities at ones without having to wait to get the whole trade executed. Thirdly, liquidity can be seen as ability to trade at low cost. (Harris 2002) Sometimes also the resiliency of the prices can be seen as a part of liquidity. In liquid markets the prices and the spread recover fast after liquidity demand shocks, e.g. large market orders, meaning that the prices are resilient. (Foucault et al. 2005) A theoretical study of Foucault et al. (2005) suggest that the proportion of impatient traders (demand immediate liquidity) in comparison to proportion of patient traders has an impact on the resiliency of a limit order market. Perfectly liquid markets on the other hand are defined so that a trader can buy and sell any amount of shares at a desired moment at the same price (Irvine et al. 2000).

In many contexts high liquidity can be seen to be related to low costs of trading (see for example (Amihud and Mendelson 1991) and (Aitken and Comerton-Forde 2003)). Amihud and Mendelson (1991) divide the costs arising from illiquidity in four components that also describe the different aspects of liquidity at some level. First component of liquidity is the bid-ask spread, i.e. the difference between the best ask and bid prices, also referred as just spread. It represents the cost of trading to the market participants and since the spread is always strictly positive[2], in effect

[1] Despite the comment of Aitken and Comerton-Forde (2003).
[2] Otherwise a trade would get executed.

a trader always loses money if first buying a stock and then immediately selling it. Thus, the smaller the spread, the more liquid the market. Secondly, the market can be seen as illiquid, if the market-impact costs of a trade are large, i.e. when trading large quantities the effect on the price is large. This means that when trading large quantities, the price is less favourable than when trading smaller quantities. The market impact can be seen as an extension for bid-ask spread since it takes into account the spread beyond the best price quotes. Third type of costs caused by illiquidity are delay and search costs that occur when trader delays the execution of a trade to accomplish more favourable terms of trading. These include the costs of finding a trading partner and the risk induced by the delay of the transaction. Lastly, high direct transaction costs of the market, e.g. exchange fees and transaction taxes, can cause the market to be illiquid. (Amihud and Mendelson 1991)

So to summarize, in liquid markets

- The cost of trading is low, i.e. the spread is small
- It is possible to execute also large trades immediately, i.e. there is enough volume
- The impact of trade size to the price is small, i.e. one does not have to pay much more per stock when buying a large amount compared to a small amount
- The spread and the price recover fast after large transaction, i.e. the market is resilient

Irvine et al. (2000) give a somewhat divergent perspective on different aspects of liquidity. First of all, to determine the period over which the liquidity is required, they separate immediate liquidity from liquidity over time, meaning that on average there can be a little liquidity available, but occasional peaks in liquidity can allow patient traders trade with low cost. Liquidity can also be categorized based on whether it is displayed or hidden. Displayed liquidity, also referred as committed liquidity, can be observed, e.g. normal limit orders represent displayed liquidity. Hidden liquidity is not observable though sometimes available, like in the case of hidden limit orders or hidden parts of iceberg orders[3]. (Irvine et al. 2000) One could assume that most of the studies concentrate on displayed liquidity since there may be more data available on that. Thirdly Irvine et al. (2000) define the liquidity to be transaction specified, since a market can be liquid for small trades while being illiquid for larger trades.

[3]For definitions see Chapter 5.4.

3.2 Measures & findings

As noted earlier, liquidity is hard to define, so one could assume that measuring it is also not that straightforward. According to Irvine et al. (2000) there is a mutual understanding in the literature that liquidity cannot be expressed by a one single variable. Thus empirical studies use a variety of different measures that capture different aspects of liquidity. (Irvine et al. 2000)

Irvine et al. (2000) divide liquidity measures into ex ante and ex post measures. Ex ante measures capture the liquidity when it becomes available, and hence are useful for traders since they give the cost at which it is possible to trade immediately. Ex post measures can be calculated once a trade has been executed. While being limited in the ability to predict the future order flow, according to Irvine et al. (2000), ex post measures can be useful for researchers studying characteristics of a market. Spread is an example of ex ante liquidity measure while effective spread, defined as

$$\text{Effective spread} = 2|\ln(P_k) - \ln(M_k)|,$$

where P_k is the price of k^{th} trade and M_k is the mid-price consolidated at the time of the k^{th} trade (Goyenko et al. 2009), is an example of ex post measure. (Irvine et al. 2000)

Liquidity measures can also be divided into trade-based and order-based measures. Trade-based measures consider for example trading value and trading volume, and they have been widely used as a result of their simplicity and the nature of data available. Still one problem related to trade-based measures is that they are ex post measures, i.e. while they can tell something about what liquidity has been in the past, they may not be able to indicate the liquidity available immediately. Automated trading systems, on the other hand, have provided the access to more detailed data about the orders and have made it possible to calculate new order based liquidity measures. Aitken and Comerton-Forde (2003) compare trade- and order-based measures of liquidity and come to the conclusion that order-based measures should be preferred, since trade-based measures can be misleading. (Aitken and Comerton-Forde 2003)

Even though there may be a mutual understanding that liquidity cannot be measured with one variable (Irvine et al. 2000), a lot of research has settled for using spread or some spread based measure as an estimate of liquidity. This is (or at least has been) understandable in the case of dealer markets, since there is traditionally available only the best quotas and the corresponding depths (Cao et al. 2009). But as the electronic limit order markets become more common and due to the reductions in the tick sizes, more of the orders have moved beyond the best quotes (Cao et al. 2009) and thus one could assume that it would be reasonable to take also other price levels into consideration. According to Rakowski and Wang Beardsley (2008), because of the recent major changes in the markets and trading, the relevance of liquidity at best ask and bid quotes has decreased and importance of limit orders beyond the best quotes has increased. Using the best quotes was appropriate in the past when spreads were wide and the depth at best quotes was large, but not any more. (Rakowski and Wang Beardsley 2008) According to Foucault et al. (2007), even though illiquidity can be interpreted as large spread, more generally it can be seen as a steeper book, indicating that price levels beyond the best ask and bid prices should be taken into consideration.

For example Chordia et al. (2002), Chordia et al. (2008), Chung and Hrazdil (2010a), Chung and Hrazdil (2010b) measure liquidity in their researches with quoted spread and effective spread. Chordia et al. (2008) find empirical results by studying large NYSE traded stocks that daily liquidity is linked to intraday market efficiency, specifically on high liquidity days the predictability of returns is significantly diminished. They suggest that high liquidity promotes arbitrage trading which in effect improves the market efficiency. Findings of Chung and Hrazdil (2010a) using more comprehensive sample also support this view. Also the empirical findings of Chung and Hrazdil (2010b) when studying NASDAQ firms confirms that market efficiency is improved by increased liquidity and this is amplified in periods with new information arrival.

Chordia et al. (2002) study NYSE traded stocks and marketwide liquidity and suggest that liquidity is also affected by extreme order imbalances, i.e. buy orders less than sell orders measured in trades. Cont et al. (2011) introduce a new variable, order flow imbalance which cumulates the sizes of order book events, i.e. market orders, limit orders and cancels. They find that the order flow imbalance is the main factor driving the price changes in short time intervals. They argue that rather than studying trades, as done in many papers, one may convey more information when studying quote updates (orders), already since the ratio of trades to quote updates in their data is 1 to 40, but also because they find that order flow imbalance drives the high-frequency price changes stronger than standard measure of trade imbalance. (Cont et al. 2011)

Roll and Subrahmanyam (2010) study the distribution of liquidity measured with spread and proportional spread, i.e. the ask price minus the bid price divided by the mid-price, marketwide. They come to the conclusion that the skewness of the distribution has increased during their 15-year sample period (while the liquidity has declined). Moreover, they compare time periods before earnings announcements (considered to have high asymmetric information) to other times and discover that the cost of trading (illiquidity) prior to earnings announcements has increased relative to other times. Goyenko et al. (2009) compare different widely used low-frequency, e.g. monthly and annual liquidity estimates that are mainly spread based, but also couple of price impact related measures and their ability to measure liquidity. Wyart et al. (2008) find in their study that spread in NYSE is significantly larger than in electronic market, thus, using specialist as a market maker appears to come with a cost as suggested at the end of Chapter 2.2. Findings of Foucault et al. (2007) suggest that the liquidity of the market can be improved by not displaying the identities of limit order traders.

A variety of measures beyond the spread have been proposed. An example of a simple liquidity measure that measures the liquidity beyond the spread is introduced by Malo and Pennanen (2012). This measure is used also in this study and is explained the in detail in Chapter 6.3. Irvine et al. (2000) propose the Cost of Round Trip trade, i.e. cost occurring when buying and selling a certain amount of shares at the same moment, to be used as measure liquidity beyond the traditional spread. Also Rakowski and Wang Beardsley (2008) use similar measure to estimate the liquidity beyond the spread. Aitken and Comerton-Forde (2003) introduce a measure that captures in addition to the bid-ask spread the order depth and the probability of order execution. There are also many other measures of liquidity developed, according to Aitken and Comerton-Forde (2003), Aitken and Winn (1997) have found 68 measured used in the literature.

4. ASYMMETRIC INFORMATION

4.1 Origins of asymmetric information

Asymmetric information in a market arises when some of the traders posses more information than the others (Harris 2002, p. 14-3). It can be the case that some traders are better able to interpret the information and hence have an informational advantage (Gajewski 1999), or the traders otherwise interpret the information differently and disagree about the value, and thus asymmetries in information arise (Rakowski and Wang Beardsley 2008). The traders in speculative markets are often divided into informed traders that trade to profit from their information and liquidity traders that trade for liquidity reasons, e.g. they need to sell or buy a stock to rebalance their portfolios (Irvine et al. 2000), also referred as uninformed traders (Anand et al. 2005). Usually both of these investor types are assumed to take liquidity, even though some of them may submit limit orders, and hence supply liquidity, to get better prices. Third type of traders is market makers. They are practically always assumed to supply liquidity, as they are trying to make profit by smoothing imbalances in order flows. (Irvine et al. 2000).

According to Anand et al. (2005) many studies have found that orders from institutions are more likely to be informed than orders from individuals and thus some studies assume that institutions are informed traders whereas individuals are uninformed (e.g. (Anand et al. 2005)). But it should be noted that also institutions trade frequently for liquidity or other non-information related reasons (Anand et al. 2005). Another type of traders that has been widely recognized to be informed is short sellers (Engelberg et al. 2012), but on the other hand it may be reasonable to assume that many of the short sellers are institutional investors rather than individuals.

In dealer markets the information asymmetry is normally indicated as differences in the information of the market maker and the traders, whereas in limit order market it is the difference in the information of the buyers and the sellers, i.e. the traders themselves (Rakowski and Wang Beardsley 2008). Bloomfield et al. (2005) show in their experimental study why, in limit order markets with asymmetric information, informed traders have advantage compared to liquidity traders when submitting limit orders (Bloomfield et al. 2005). Naturally, all traders that submit limit orders face execution risk (Bloomfield et al. 2005), e.g. the risk that the limit order may or may not get executed and the execution time is uncertain (compare to market orders which guarantee the execution of the order as discussed in Chapter 1) (Parlour and Seppi 2008). However, while liquidity traders do, informed traders with superior information do not face adverse selection risk when submitting limit orders. Adverse selection risk means that limit orders generating loss rather than profit to the submitter are more likely to get executed. Due to adverse selection, the risk when submitting a limit order is lower for informed traders with superior information as for liquidity traders. This indicates why in some situations informed traders have an incentive to submit limit orders, i.e. supply liquidity, in the contrast to the common view that informed traders only take liquidity. Moreover, Bloomfield et al. (2005) find in their study that both informed and liquidity traders submit limit orders as well as market orders, but actually informed traders use more limit orders on average than liquidity traders. The behaviour of the informed traders seems to respond to the change in the price: when the price deviation from the true value is large, informed traders submit market orders, i.e.take liquidity, but as the price gets close to the true value, informed traders shift to supplying liquidity and in effect take the role of a market maker. (Bloomfield et al. 2005)

Many researchers have developed methods to identify the adverse selection component (cost of information asymmetries) of spread. Many of the models are also concentrated on market makers and hence do not apply on electronic limit order markets. Nevertheless, some models have also been developed to limit order markets, but they do not necessarily consider the limit order book beyond the spread. (Rakowski and Wang Beardsley 2008) Wyart et al. (2008) develop a theoretical model which they test empirically and argue that the main factor of spread is actually adverse selection.

Rakowski and Wang Beardsley (2008) empirically investigate information asymmetries in a limit order market and develop a model to decompose liquidity (cost of trading) throughout the book into asymmetric information and non-information components. Their findings are consistent with that informed traders submit relatively competitive limit orders in addition to market orders, but not that many further back in the queue (Rakowski and Wang Beardsley 2008), which also Linnainmaa (2005) found in his study. Findings of Rakowski and Wang Beardsley (2008) are also consistent with most research on information asymmetries, as they find that actively traded stocks have less information asymmetry since they are widely followed and studied by analysts. But information asymmetries in the books of actively traded stocks seem to persist deeper in the book, while for inactive stocks the information asymmetry drops sharply after the inside quotes. This is interpreted so, that whereas the informed traders of active stocks are able to hide their limit orders in the larger order flow from liquidity traders and get executed also further from the best quotes rather quickly, the informed traders of inactive stocks cannot hide their orders and thus must take advantage of their information as soon as possible by submitting market orders or aggressive limit orders. (Rakowski and Wang Beardsley 2008)

According to Ahn et al. (2001), the main difference between informed trading and liquidity trading is that while informed trading causes permanent price changes, liquidity trading leads to temporary changes in price. Hence executing limit orders against liquidity traders is profitable whereas trading against permanent price changes caused by informed trading is undesirable. (Ahn et al. 2001) Transitory volatility refers to the part of volatility of stock prices that is caused by the trading of uninformed traders rather than unanticipated changes in value of the stock (Harris 2002). Ahn et al. (2001) study pure a order-driven market and discover that depth of the market increases in response to increase in transitory volatility and transitory volatility decreases subsequent to increase of depth of the market. They also compare submission of limit and market orders and observe that when transitory volatility arises from the ask (bid) side of the book, traders tend to enter more limit sell (buy) orders than market sell (buy) orders, i.e. limit orders are submitted when liquidity is needed. However, they found no evidence that the depth of the book beyond the best quotes has an impact but based on their study it seems that depth at the best quotes is what matters. (Ahn et al. 2001)

Cao et al. (2009) evaluate the information content of a limit order book. The results suggest that the order book beyond the best quotes is moderately informative. They also find that order imbalances between the two sides of the book relate significantly to the short-term returns of the future, especially when the imbalances are extreme. Moreover, partially based on former literature, they suggest that order activities at or near the best quotes may not be related to new information. Thus, orders further away from the best quotes could be related to less noisy and more stable information. (Cao et al. 2009)

Foucault et al. (2007) study the effect of anonymity in limit order markets. It is quite intuitive that since the trader identities can reveal something about the information level of the traders and their orders, they may reveal something about the risk of being picked-off for the uninformed traders. Hence, revealing or concealing the trader identities may have an effect on the behaviour of uninformed traders. Foucault et al. (2007) develop a theoretical model and, by comparing data from

Paris Bourse (electronic limit order market) before and after the change to conceal the trader information, they obtain that the spread and its informativeness about future volatility of the price are significantly smaller after the change. Hence, they argue that both public and private information about the price volatility are reflected in a limit order book, i.e. the information is asymmetric. (Foucault et al. 2007)

4.2 Information asymmetries around news announcements

Gajewski (1999) proposes two hypothesis concerning asymmetric information after earnings announcements. According to the first one, there may be traders that know the content of the announcement already before the announcement gets published. Since the disclosure of the earnings invalidates the informational advantage, traders who posses the information must take the advantage of it before the announcement, and the disclosure should reduce information asymmetries. Hence the earnings announcements should be followed by higher liquidity[1]. (Gajewski 1999)

According to the second hypothesis proposed by Gajewski (1999), some investors ability to process the information included in the earnings announcements is overwhelming compared to others and hence the disclosure of earnings announcements in fact increases the informational asymmetries. This leads to lower liquidity after the announcements. (Gajewski 1999) The results of empirical study of Gajewski (1999) show that information asymmetries increase around earnings announcements and are otherwise consistent with this second hypothesis, but as they also discover that the trading volume increases, they suggest that other effects have an impact.

Also Engelberg et al. (2012) rise similar hypothesis from the literature and report that the literature is divided in two. Others predict that news events decrease information asymmetries while others argue that news events increase asymmetric information (Engelberg et al. 2012). In their study Engelberg et al. (2012) find support on the second view as did Gajewski (1999). Study of Sandås (2001) suggests that there may be a delay between release of new information and adjustment of the limit order book.

Engelberg et al. (2012) study the trading behaviour of short sellers around news releases and the study indicates that the trading advantage of short sellers comes mainly from their ability to analyze publicly available information. They find that short sellers do not anticipate news but trade on or after the dates of news releases.

[1] According to Gajewski (1999) "the earnings announcements should be followed by tighter spreads, a lower impact of transactions on prices and larger trading volume" which in this context can be interpreted as better liquidity.

But since they are using daily level observations, in the context of this study we cannot interpret their findings to mean that it would be less likely that there is informed trading right before the release of the announcement than after the announcement. They also do not find clear evidence that the liquidity would increase on days of news releases. (Engelberg et al. 2012)

Linnainmaa (2005) gives many intriguing insights about information asymmetries and investor behaviour around earnings announcements. He studies the importance of limit order effect, that is, it appears that the reaction of limit order traders to new information, e.g. publishing of earnings announcement, is quick but incorrect. According to Linnainmaa (2005) the evidence in the literature suggests that the individual investors watch markets closely but consistently misinterpret the new information leading to losses. His study however shows that the use of limit orders can explain the somewhat puzzling behaviour of individual investors: rather than individual investors reacting quickly to the news, institutional (informed) investors react fast entering market orders which trigger the stale limit orders of individual (liquidity) traders and in effect it seems that individual investors misinterpret the information and trade actively, while in reality they are passive or too slow to cancel their stale limit orders before they get executed. The study shows a sudden change in the behaviour of institutional investors around the of earnings announcement: before the announcement institutions supply liquidity to the market but after the arrival of the announcement rather than supplying liquidity they take it by submitting large amounts of market orders. (Linnainmaa 2005)

The limit order effect observed by Linnainmaa (2005) also gives an explanation for attention-grabbing behaviour of individual investors studied by Barber and Odean (2008) (Linnainmaa 2005). Attention-grabbing behaviour refers to limited ability of individual investors to monitor all the stocks, leading investors to buy stocks that grab their attention, e.g. are in the news (Barber and Odean 2008). The findings of Linnainmaa (2005) suggest that what appears to be individual investors attention grabbing behaviour actually mostly arises from the passive limit orders of individual investors (Linnainmaa 2005).

Moreover, Linnainmaa (2005) finds that individual investors use significantly more limit orders, whereas institutional investors earn large gains from the limit orders of individual investors. He also observes that the use of limit orders differs also otherwise when comparing individual and institutional investors. While individual investors usually place their limit orders outside the spread, institutional investors tend to place their limit orders inside the spread, close to the other side of the book and hence use the limit orders mostly as substitutes for market orders. (Linnainmaa

2005)

Consistent with this, Mu et al. (2010) find evidence in their study of the order flow in limit order market around extreme intraday price changes, that the strategies of institutions are more aggressive and their behaviour differs from that of individual traders. They conclude that institutional investors have more important role in driving large fluctuations in prices and that they are better informed than individual traders. They also observe significant overreaction around intraday decreases and increases in prices, after which the price somewhat stabilizes, but the price impact is permanent. (Mu et al. 2010)

5. MARKET ARCHITECTURE OF NASDAQ OMX NORDIC

5.1 Markets studied

In this study there are stocks included from three stock exchanges: Helsinki Stock Exchange (OMX Helsinki), Stockholm Stock Exchange (OMX Stockholm) and Copenhagen Stock Exchange (OMX Copenhagen). They are all part of NASDAQ OMX Nordic. For all the relevant parts presented in the following sections of this chapter the markets are similar for all Helsinki, Stockholm and Copenhagen exchanges. For additional details about the market models of exchanges see (NASDAQ OMX Nordic 2011). The analysis in this chapter is structured according the market architecture concept introduced in Chapter 2.2.

5.2 Market type of NASDAQ OMX Nordic

NASDAQ OMX Nordic market is a continuous limit order based market. During continuous trading, automatic order matching system compares each submitted order to the orders on the opposite side of the book, and matches buy and sell orders if the price, volume and possible other specifications correspond. The orders can be either fully executed or they can be executed partially in one or more steps. (NASDAQ OMX Nordic 2011)

The market also exploits call auctions at the beginning and end of the trading day and in the case of trading halts (NASDAQ OMX Nordic 2011). This is a common practice in continuous markets, since the uncertainty over the fundamental value of a stock can be large at the open and close and also in the case of re-opening the continuous trading after trading halts, and call auctions appear to be effective when aggregating diverse information in uncertain situations (Madhavan 2000). The call auction consist of two parts. In the first part, i.e. order management, managing the already submitted orders, e.g. canceling the order or reducing the volume, as well as submitting new orders, is allowed, but no automatching takes place. The second phase is called uncross. In the uncross an equilibrium price that maximizes the number of shares traded[1] is determined, and all orders with more generous price than the equilibrium price get executed at the equilibrium price[2]. (NASDAQ OMX Nordic 2011)

NASDAQ OMX Nordic Equities market does not rely on market makers, but all the market participants trading in the market must be authorized to trade. In practice the members of NASDAQ OMX Nordic have the right to trade. NASDAQ OMX Nordic divides the users into tree categories for which the trading rights can be given. First of all the trading personnel of members of NASDAQ OMX Nordic can be given the right to trade. Members are also entitled to automatically route the orders of their clients. Lastly members are also allowed to use automatic trading, e.g. use softwares that automatically create orders based on some market signals. (NASDAQ OMX Nordic 2011)

5.3 Price discovery in NASDAQ OMX Nordic

The price discovery process of NASDAQ OMX Nordic market is independent and based on the orders submitted by the traders. Nevertheless, NASDAQ OMX Nordic offers order routing during continuous trading. This means, that if the best price is not available in the market, the submitted order is routed to other markets that are supported, to try to execute the order there instead. If the matching in other markets is not possible, the order is routed back to the Nordic market and posted there. (NASDAQ OMX Nordic 2011)

5.4 Permitted order forms in NASDAQ OMX Nordic

There are essentially three types of permitted order types in NASDAQ OMX Nordic market. These are limit order, market order and imbalance order. Additionally there are some order attributes and time constraints that can be used to change the nature of the orders. (NASDAQ OMX Nordic 2011)

Limit orders, as already discussed earlier, have the maximum (minimum) bid (ask) price and quantity. Limit orders can never execute on worse price than the specified limit price. When submitted, if the limit order does not get fully executed immediately, the remaining part is added to the queue of orders in the book. (NASDAQ OMX Nordic 2011)

[1]For details about cases where more than one such prices exist see (NASDAQ OMX Nordic 2011).

[2]For the case of imbalance in the orders at equilibrium price see (NASDAQ OMX Nordic 2011).

As also discussed earlier, market order is an order to sell or buy a specific quantity of the stock at the market price, i.e. the best bid or ask price available, respectively. The market order will only execute at the best price level and hence if there is not enough volume available at the best price, the remaining part of the order will be canceled, even if there would be volume available at a worse price. But it should be noted that if one wants to sweep through multiple price levels, it is possible to use a limit order with a price that crosses the best price. (NASDAQ OMX Nordic 2011)

The third type of order, imbalance order, can only be used in the opening and closing call auctions briefly discussed earlier. An imbalance order accepts the equilibrium price determined in the uncross and can only get executed against surplus left after filling other orders in the uncross. (NASDAQ OMX Nordic 2011) That is, the imbalance order gets executed only in the case that there is imbalance in the orders at the equilibrium price, for example in a simple case where there are two orders at the determined equilibrium price, one sell order of two shares and one buy order of one share. If there is a imbalance buy order of one share, in this case it gets executed. On the other hand, if an imbalance sell order of one share exists, it does not get executed since there is no surplus on the buy side.

The permitted order forms can be modified to some extent by combining them with order attributes[3]. In the case of a reserve order, also called iceberg order, a part of the order is displayed for other traders and rest of the order is hidden. When entering a reserve order the trader determines the proportion of the total order that will not be displayed in the order book. Still both displayed and non-displayed portions of the order can be matched with incoming orders and hence get executed. When the displayable cut of the order gets fully executed, a part of the non-displayable cut is to be sent to the order book as displayable. Also non-displayed, hidden orders are possible, which means that only the market participant submitting the order can see it. But to be submitted as non-displayed, the order must be large enough in comparison to average daily turnover of the stock. (NASDAQ OMX Nordic 2011)

A pegged order has a price relative to the current market price. The price can be set to be desired amount of ticks higher or lower than the best offer in the book, and in this case the order can be either displayable or non-displayable. It is also possible to choose mid-point peg, which means that the price is set to be the mid-point of the best current ask and bid price, i.e. the mid-price, but the mid-point peg orders can never be displayed. Pegged orders get adjusted every time the best offers in the the book change, but it is also possible to give a limit price beyond which the order

[3]For details about which attributes can be combined with each other see (NASDAQ OMX Nordic 2011).

will not get executed. It is important to notice that the rules concerning the non-displayed orders also apply to pegged orders: to be non-displayed, also the pegged order must be large enough. (NASDAQ OMX Nordic 2011)

Lastly there are minimum quantity orders. Minimum quantity orders have a minimum share quantity under which the order cannot be executed. To be non-displayed, minimum quantity order must also be large in scale. (NASDAQ OMX Nordic 2011)

NASDAQ OMX Nordic allows alltogether five different time constraints to be set on the orders submitted. Immediate-or-cancel (IOC), also called Fill and Kill (FAK) orders, can be executed only at the time of the entry. If the order or a part of it cannot be executed immediately, the remainder of the order will be canceled. Good-till-market close and Day orders are essentially (at the moment) the same, they are valid for the current trading day and after the market close the remaining part of the order gets canceled. Good-till-cancelled (GTC) orders are valid until canceled and will be inserted in the book again in the next morning if left over night. A Good-till-time (GTT) order is valid till a specific time of the current trading day. (NASDAQ OMX Nordic 2011)

5.5 Protocols of NASDAQ OMX Nordic

Here we go through some of the most important trading protocols used in NASDAQ OMX Nordic. The orders in the order book of NASDAQ OMX Nordic are matched under price-internal-display-time priority. This means that submitted orders with better prices are always matched first. Then, if orders are at the same price level, an incoming order is first matched with same member's orders (internal), then with displayed orders and last with order with the earliest time stamp, e.g. order submitted earliest. (NASDAQ OMX Nordic 2011)

Trading halts can take place for two reasons. First of all the trading can be halted due to technical reasons if a considerable proportion of the members lose connection to the market. Second, the trading can be halted for regulatory reasons if there is a risk of unfair market conditions, meaning that "trading will no longer be carried out on equal terms or will not be based upon sufficient information". (NASDAQ OMX Nordic 2011)

After a trading halt the trading can be resumed with a call auction already discussed earlier, or with flushing the order book. Flushing is used when there is a possibility that there are orders in the book reflecting market price before a corporate action with a relatively large impact on the price. That is, flushing is used to avoid trades being executed at price levels other than current market price and to protect market participants from trading at outdated prices. In practice, during the flush, all the orders regarded to be outdated in terms of price are canceled. (NASDAQ OMX Nordic 2011)

NASDAQ OMX Nordic relies on volatility guards in avoiding trading incidents and reducing impacts of sudden and extraordinary orders. An order that deviates too much from the price of the last trade in the case of dynamic volatility guard or from the reference price in the case of static volatility guard, triggers the volatility guard halting the continuous trading. The trading halt is followed by a call auction, after which the continuous trading is resumed. (NASDAQ OMX Nordic 2011)

NASDAQ OMX Nordic also offers an optional pre trade risk management service for its members. The service can be used to prevent market participants (members and their clients and customers) from submitting incorrect orders. Members can define what orders should be allowed and the service validates all the orders submitted before they are tried to match. (NASDAQ OMX Nordic 2011)

5.6 Transparency of NASDAQ OMX Nordic

During the continuous trading all the orders in the order book excluding the non-displayed orders are disseminated for all the market participants. Also the trades are published in real-time, and the counterparty information is given in Stockholm and Copenhagen as well as for most order books in Helsinki exchange. All counterparty information is published at the end of the trading day. In order management phase before uncross there is available the equilibrium price, volume traded, imbalance volume and direction, the best bid and ask prices (they are equal to equilibrium price if it exists) and bid and ask volumes at best prices or aggregated at equilibrium price in case the book is crossed. (NASDAQ OMX Nordic 2011)

6. DATA

6.1 Limit order book data

This study has data about the state of the limit order book for alltogether 75 different stocks. 27 of them are traded in Helsinki Stock Exchange (OMX Helsinki), 28 in Stockholm Stock Exchange (OMX Stockholm) and 20 in Copenhagen Stock Exchange (OMX Copenhagen). List of all stocks included in this study can be found in appendix A. The stocks chosen to be studied have belonged to following NASDAQ OMX indexes: OMX Helsinki 25, OMX Stockholm 30 and OMX Copenhagen 20. The stocks studied belonged to the indexes either at the end of 2013 or in 2009, or, as in many cases, they were part of the index at both times. If an index included more than one stock from the same company traded in the same exchange, the stock which was more traded was chosen to be included. There are also a couple of stocks that are traded in different currencies in different stock exchanges, whom were included in this study. The stocks belonging to these indexes were chosen because they can be regarded as frequently traded stocks. As later on in this study the changes in the liquidity of a stock with ten second time interval is researched, the stocks that experience frequent changes in liquidity, i.e. are traded frequently, are of interest. This delimits the results to apply only to frequently traded stocks.

The study has limit order book data for all stocks to be studied from 1.1.2006 to 1.1.2010 for all the trading days[1] with ten second time interval. The data used includes twenty best bid and ask prices with corresponding quotes. Twenty price levels are used because they are available, but the choice is somewhat arbitrary and using e.g. 10 best price levels instead may have some influence on the findings. For most of the stocks traded in OMX Helsinki and OMX Stockholm there are 977 trading days per company and in OMX Copenhagen 974 trading days in the four year sample period. The stock exchanges in Helsinki and in Stockholm are opened 9:00-17:30 Central European time and in Copenhagen 9:00-17:00 (NASDAQ OMX Nordic 2011), so the first observation of a day in our data is in all the exchanges at 9:00:10 Central European time and the last observation for Helsinki and Stockholm is

[1] Excluding trading days when technical errors have occurred and the data could not be collected.

at 17:30:00 and for Copenhagen 17:00:00. From the data it is possible to distinguish the moments when trading halts occurred and those moments are not taken into consideration in this study since normal trading and auto matching of the orders are halted during those moments.

6.2 News data

The news data used in this study is collected from Nasdaq website[2] and contains all the corporate announcements that were filed with NASDAQ OMX by the respective companies included in this study during 1.1.2006-1.1.2010. The corporate announcements are categorized in 32 different categories. In this research we study the earnings announcements, since earnings are a crucial factor when determining the value of a company and information of the earnings allows the traders to better forecast the results of a company (Gajewski 1999). Moreover, the publication of earnings announcements is expected so they provide an interesting subject of study how the market behaves before and after the disclosure.

To pick the earnings announcements from the categories, the study chooses quarterly reports, interim reports and half year financial reports, which can all be interpreted as regularly published reports from the companies. The reason only one category, for example quarterly reports, is not chosen is that for example in the case of Nokia the quarterly reports are categorized as quarterly reports before year 2008, but from 2008 onwards they are categorized as interim reports. So the categorization of the corporate announcements is not perfect, and in fact even for Nokia one quarterly report published during the four year period is categorized more broadly as company announcement.

The data set contains announcements published in many languages, and in the case there exists more than one announcement per day for a specific company only the first one is included in the study. It should be noted that the categorization is also not perfect in the sense that all the announcements we end up with are not in reality releases of earnings announcements, because there are companies for which we get more than 16 news announcements when the maximum amount should be four per year, i.e. alltogether maximum of 16 pieces of news for the four year period. Alltogether the sample consists of 971 corporate announcements that are considered to be earnings announcements. The numbers of news per companies are reported in the appendix A.

[2]http://www.nasdaqomxnordic.com/news/companynews, see the page also for detailed information.

6.3 Modeling liquidity of a limit order book

As done by Malo and Pennanen (2012), by interpreting buy orders as sell orders of negative quantity, we can describe the state of a limit order book with marginal price curve $s(x)$, which is piecewise constant and nondecreasing function of order quantity. Marginal price curve gives us the price of the last share bought (positive quantity) or sold (negative quantity) in a batch depending on how many shares are bought or sold alltogether. (Malo and Pennanen 2012) In figure 1 we can see an example of a marginal price curve for Nokia stock at a specific moment with twenty best bid and ask price levels (the black piecewise constant line). If the markets were perfectly liquid, marginal price curve $s(x)$ would be constant line (Malo and Pennanen 2012), which means that one could buy or sell as many shares as one wants with a constant price.

To be able to define the liquidity measure used in this study we first need to define mid-price. Mid-price, sometimes also referred as "market price", is defined as follows:

$$\bar{s} := \frac{s^b + s^a}{2},$$

where s^b is the best bid and s^a the best ask price (Malo and Pennanen 2012). The mid-price can change if orders on either side of the book get executed or if the best bid or ask order get canceled or replaced by a better offer.

To study the liquidity of a limit order book rather in monetary units than in numbers of shares, this study uses a simple monetary measure of illiquidity $r(h)$ presented by Malo and Pennanen (2012). $r(h)$ is defined by the function

$$r(h) := \ln(\frac{s(h/\bar{s})}{\bar{s}}) = \ln(s(h/\bar{s})) - \ln(\bar{s}),$$

where $h = \bar{s}x$ is the mark-to-market value of a market order of x shares, i.e. the value of the market order if we were to pay the mid-price for all the shares. So $r(h)$ gives the percentage change in the marginal price $s(x) = s(h/\bar{s})$ relative to the mid-price $\bar{s}$, as a function of h, mark-to-market value of an order of x shares. Hence $r(h)$, also called relative price impact curve, presents what kind of temporary price impact a market order would have on the best offers. In other words using $r(h)$ one could calculate the relative change in best bid or ask offer when selling or buying a certain amount of shares. (Malo and Pennanen 2012) Figure 2 gives an example of relative price impact curve for Nokia stock at a specific moment.

As marginal price curve $s(x)$, also relative price impact curve $r(h)$ is always nondecreasing, but in addition to that, $r(h)$ passes always through the origin. Steeper

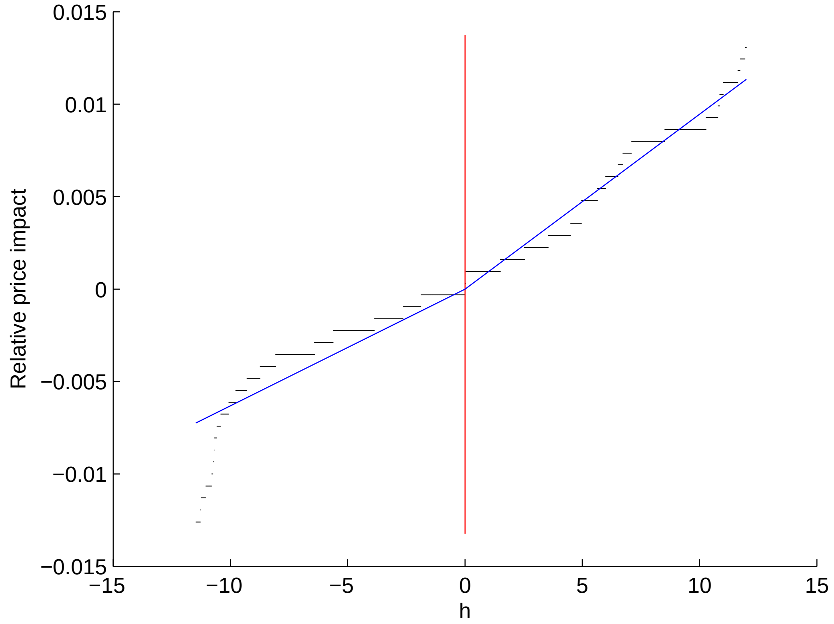

Figure 2: The relative price impact curve $r(h)$ with its two sided linear approximation for Nokia 3.1.2006 at 15:59:30. The black piecewise constant line corresponds to $r(h)$ and blue solid lines correspond to the linear approximations of $r(h)$ on both sides of the book.

the price impact curve $r(h)$ is, less liquid the stock is. On the other hand, if the markets are perfectly liquid, the price impact curve $r(h)$ is zero by definition. (Malo and Pennanen 2012)

Classical perfectly liquid market models assume that the price of a share does not depend on how many shares one buys or sells, which means that the limit order book can be modeled by horizontal line passing through the mid-price $\bar{s}$, which implies that $r(h)$ is zero (Malo and Pennanen 2012). Malo and Pennanen (2012) propose that the shape of limit order book can be modeled somewhat more accurately but still simply by modeling the relative price impact curve as a linear function passing through the origin. The model is form

$$r(h) = \beta h,$$

where β is positive and can be considered to be a measure of overall liquidity of the stock. The smaller β the more liquid the stock is. (Malo and Pennanen 2012)

This study uses β for studying the liquidity of the limit order book. Since the values of $r(h)$ and h are known for each moment, the study uses simple linear regression to calculate the values for β. When determining the values for β twenty best ask and bid price levels are taken into consideration[3]. Since the values of β in two sides of the book can be significantly different (Malo and Pennanen 2012), own values of β for bid and ask sides of the book are calculated, represented by β_{Bid} and β_{Ask}, respectively. In figure 2 the blue solid lines are linear approximations of two sides of relative price impact curve and the slopes of the lines are β_{Bid} and β_{Ask}. β of a limit order book, i.e. the liquidity of a stock, can change when new limit orders are submitted or old ones get executed or canceled.

The study also compares liquidity measured with β to liquidity measured with traditional spread around earnings announcements. It is important to notice that these liquidity measures are essentially describing liquidity for different kinds of trades. Whereas β measures the liquidity and costs arising from illiquidity for large trades sweeping over many price levels, spread measures the liquidity and costs of small transactions that take place only at the best quotas.

6.4 Example of order book around earnings announcement: case Nokia

As an example of how the changes in liquidity can affect the shape of a limit order book or, the other way around, how changes in the shape of an order book affect liquidity, the study now presents one example stock and chooses one example earnings announcement release and plots the evolution of liquidity, i.e. β around the release of the announcement and plots the order book at a few points in time around the announcement. As an example the study chooses Nokia's stock and earnings announcement released 16.10.2008 at 12:00:4 o'clock. As the time of the event is estimated to be the closest observation moment of the study, it is assumed that the event actually takes place at 12:00:00. Figure 3 plots β and the mid-price around the earnings announcement and the order book ten minutes before the event, ten seconds after the event[4] and ten minutes after the event.

In Figure 3, we can see that ten minutes before the event the liquidity is somewhat lower, i.e. β is higher, than on average during the previous 27 days. Ten seconds after the event liquidity is notably lower, i.e. β is higher, than on average or ten minutes before the event. When comparing the shape of the order book ten minutes before the event and ten seconds after the event we can see that in the latter case the book is thinner on both sides of the book meaning that the quantity available to

[3]Or in case there are not twenty different price levels in one side of the book, as many as are available.

[4]Or strictly speaking six seconds after the event since the actual announcement time was 12:00:04.

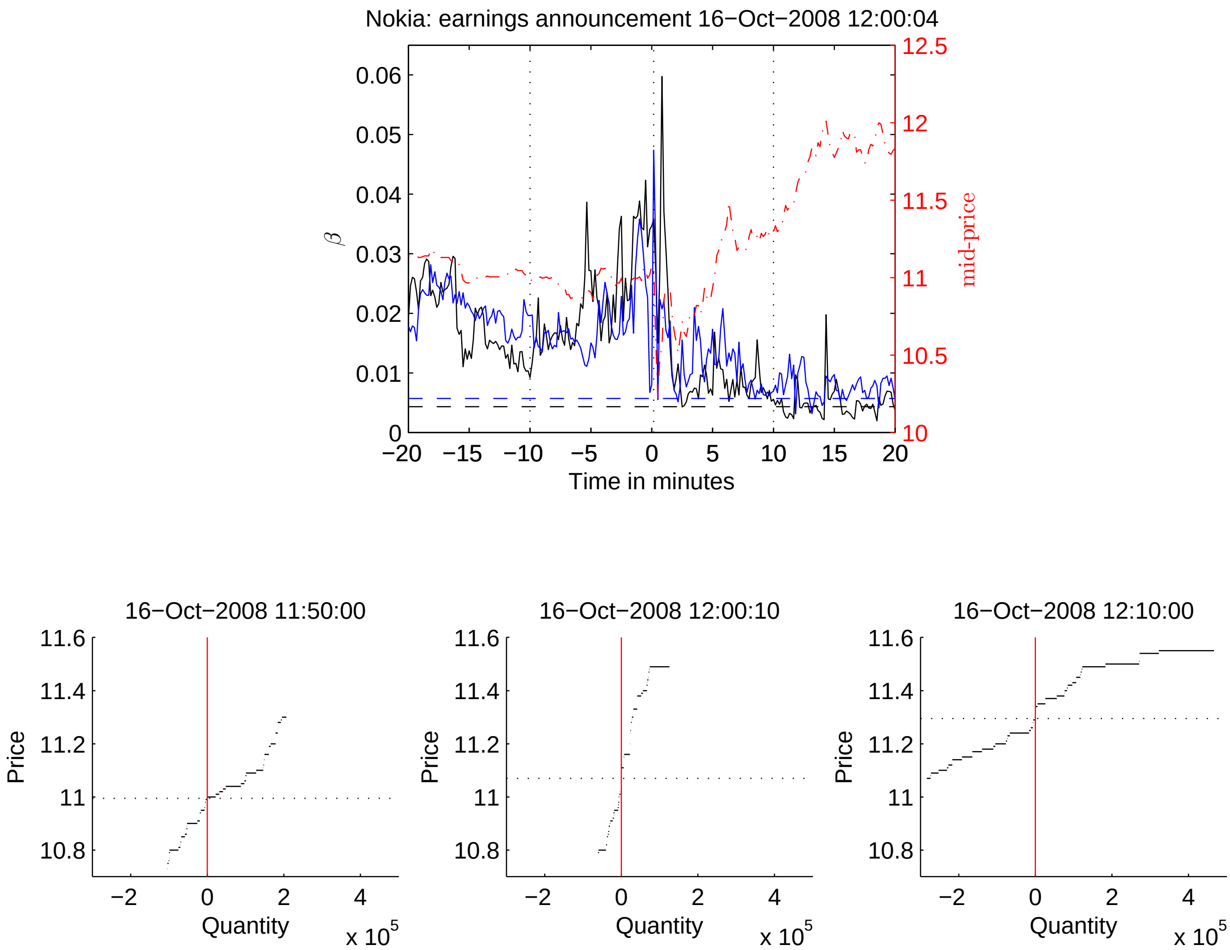

Figure 3: β of Nokia around earnings announcement on 16.10.2008 at 12:00:04 (estimated to take place at 12:00:00) and three examples of order book around the announcement. In the upper figure the event occurs at time 0 and black solid line corresponds to β on the ask side and blue solid line to β on the bid side and the black dashed line and the blue dashed line represent the average β during 27 previous days of the announcement on ask and bid sides respectively, all with scale on the left hand side with black. The red dash-dot line corresponds to the mid-price around the earnings announcement with scale on the right hand side. The dotted black lines represent the times of the order books plotted in the three figures below at ten minutes before the event, ten seconds after the event and ten minutes after the event.

sell and buy has reduced, i.e. orders have been executed or canceled. The mid-price has also increased slightly as a respond to the orders shifting upwards. Ten minutes after the event the liquidity seems to be roughly at the normal level, and, as we can see from the order book, there is much more quantity available on the both sides of the order book than in either of the previous cases. The book has also shifted further upwards leading to the increase in mid-price and the price ranges have narrowed at least on the ask side of the book. If one would fit a line intersecting at mid-price on both sides of the book in all three cases, one would notice that the slope would be steepest ten seconds after the event when the liquidity is at its worst and the slope is most gradual ten minutes after the event when the liquidity is at its normal level.

6.5 β and $\ln(\beta)$

Figure 4 shows the observed β for both bid and ask side of the order book of Nokia for the four-year period 2006-2009. We can clearly see in Figure 4 that the distribution of β does not remain the same for the entire period, but the variation is much larger in the last two years of the period than in the first two for the Nokia stock. This is one reason why this study does not use parametric methods in studying the behavior of the limit order book in the following chapters, but non-parametrics instead, and why the whole sample period is not used to to determine the normal behaviour of β. In Figure 5, which presents the calculated $\ln(\beta)$s for the same period, we can also conclude that the same holds for $\ln(\beta)$ since the mean does not remain the same.

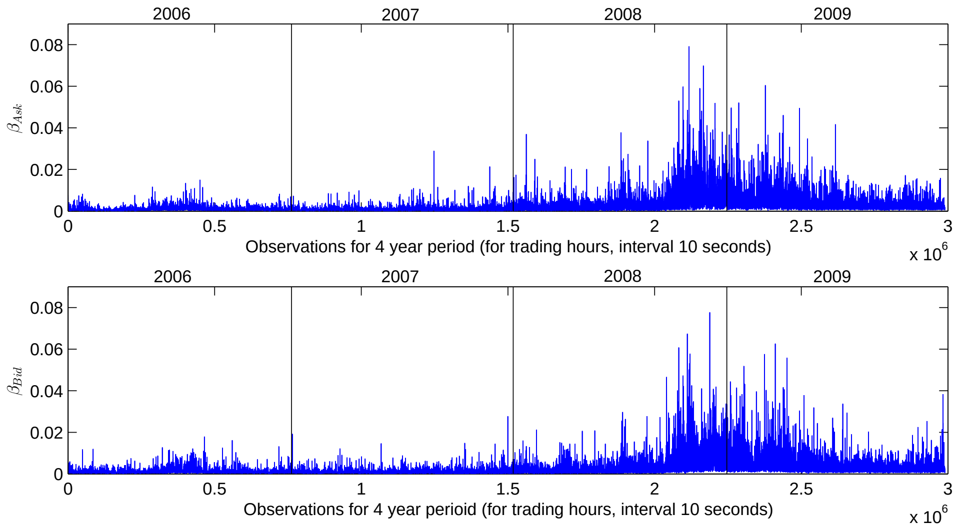

Figure 4: β for the order book of Nokia between 2006-2009 with 10 second time interval for all trading hours. The black solid lines mark the first observations of each year.

In figure 6 we can also see why fitting the data in some known distribution may cause some problems. At least the distributions of $\ln(\beta)$s with two unsymmetrical peaks each do not resemble any known distribution and in any case both β's and $\ln(\beta)$'s distributions are far from the optimal case where they would be normally distributed. Nevertheless, it may be possible to successfully fit a gamma distribution

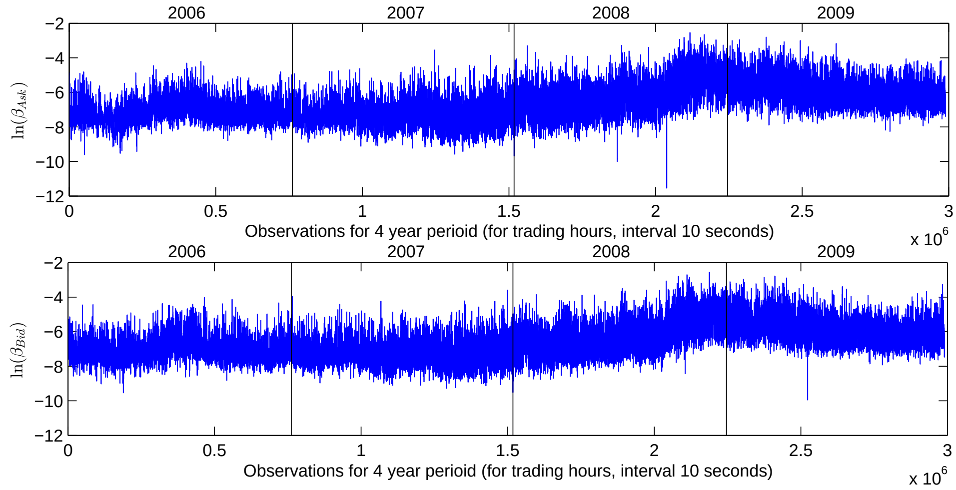

Figure 5: ln(β) for the order book of Nokia between 2006-2009 with 10 second time interval for all trading hours. The black solid lines mark the first observations of each year.

or exponential distribution to β. However, since the values of β and ln(β) are strongly autocorrelated[5], being able to fit a known distribution would not solve all the problems related to using parametric methods.

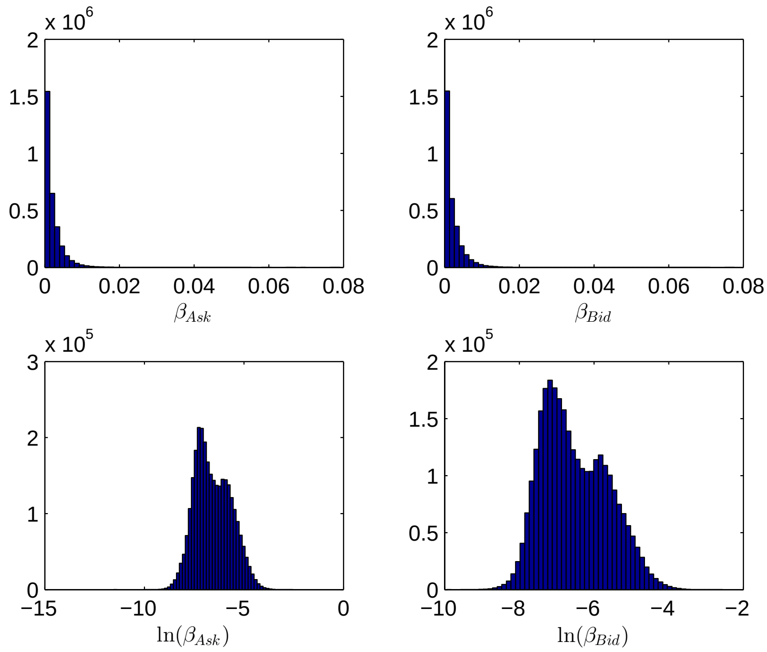

Figure 6: The histogamm for β and ln(β) for the order book of Nokia between 2006-2009 with 10 second time interval for all trading hours

Figure 7 shows an interesting case. When dividing the four-year period 2006-2009

[5]The values of β and ln(β) are dependent on the previous values

into to two two year periods 2006-2007 and 2008-2009, we can see that the distributions of $\ln(\beta)$s are quite close to normal. This may indicate that there has been some more radical change around 2007 and 2008. But this is only the case for the Nokia stock. For example, for Stora Enso it seems that there is some minor fluctuation in the mean of $\ln(\beta)$, but the distribution does not seem to have two peaks. Then, for Nordea there seems to be a bit more fluctuation in the mean and there may also be more than one peak, but the change does not seem to happen necessarily at the same time as in the case of Nokia, since also in the histograms of two year observation one may distinguish two peaks. For TeliaSonera there are two notable peaks in the distribution of observations of all four years, but as with Nordea, the change does not seem to happen quite at the same time as with Nokia since the peaks more or less persist when dividing the period in two.

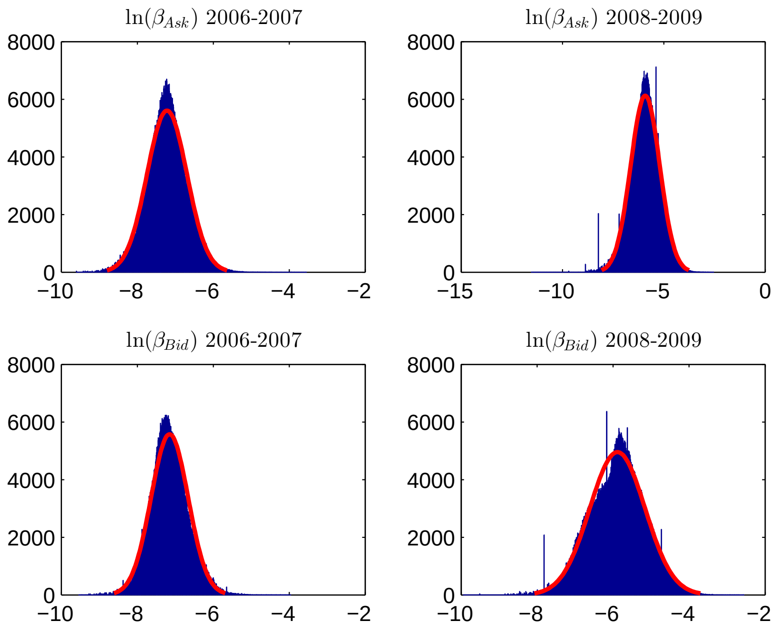

Figure 7: The histograms for $\ln(\beta)$ on ask and bid sides with normal distribution fit plotted with red for 2006-2007 and 2008-2009

One more interesting thing related to Figure 5 and the other examples briefly discussed is that when comparing $\ln(\beta)$s over the four year period, it seems that for all the four companies the fluctuation of the mean seems to have somewhat same trend. So the variation in $\ln(\beta)$ may be somehow dependent on the situation of the market as a whole, and not just be company-specified. This may indicate that it would be possible to smooth the data by first observing the trend in the market and then using it to standardize $\ln(\beta)$. This also gives a light support on findings of Chordia et al. (2000) and Huberman and Halka (2001) among others, who have observed that liquidity has a time varying common component over different stocks.

6.6 Changes in β and $\ln(\beta)$

We noticed in the previous subsection that studying β or $\ln(\beta)$ is somewhat difficult. Hence, we now take a look at the changes in β and $\ln(\beta)$. The change in β, $\Delta\beta$, represents the absolute change in the value of β and is calculated by

$$\Delta\beta_t = \beta_t - \beta_{t-1}.$$

The change in $\ln(\beta)$, $\Delta\ln(\beta)$ is the relative change of β, and is calculated by

$$\Delta\ln(\beta_t) = \ln(\beta_t) - \ln(\beta_{t-1}) = \ln\left(\frac{\beta_t}{\beta_{t-i}}\right).$$

In Figure 8 we see $\Delta\beta$ for the four-year period. As in the case of β and $\ln(\beta)$, also for $\Delta\beta$ it seems to hold, that the distribution does not remain the same for the whole period. But as we notice in Figure 9, for $\Delta\ln(\beta)$ it is not that clear anymore. So if one was just to study the relative change in β it may be possible to make conclusions by comparing the behaviour of the book around news events to the behaviour of the book during the whole period.

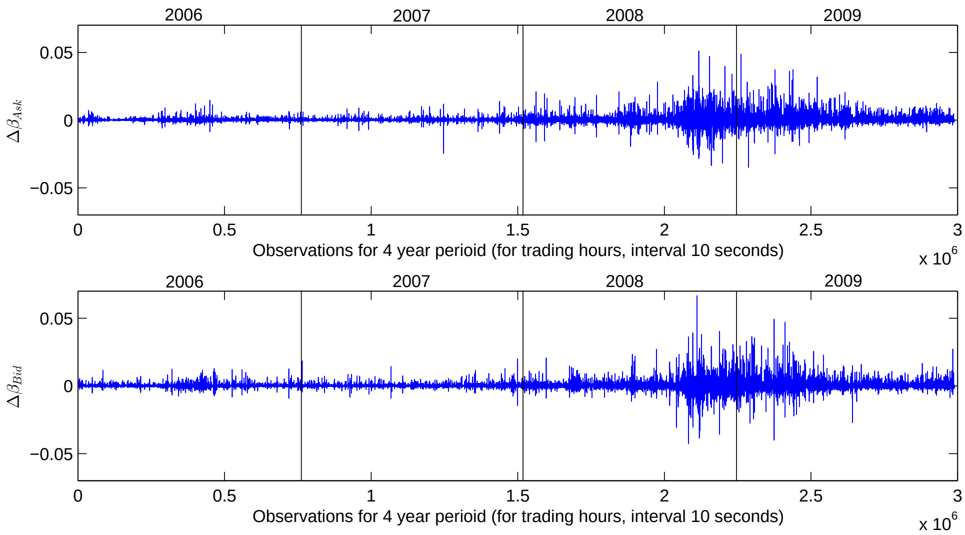

Figure 8: The change in β for the order book of Nokia between 2006-2009 with 10 second time interval for all trading hours. The black solid lines mark the first observations of each year.

Figure 10 shows the histograms for $\Delta\beta$ and $\Delta\ln(\beta)$. In Figure 10 we can see that both $\Delta\beta$ and $\Delta\ln(\beta)$ are fairly symmetrically distributed around zero with rather

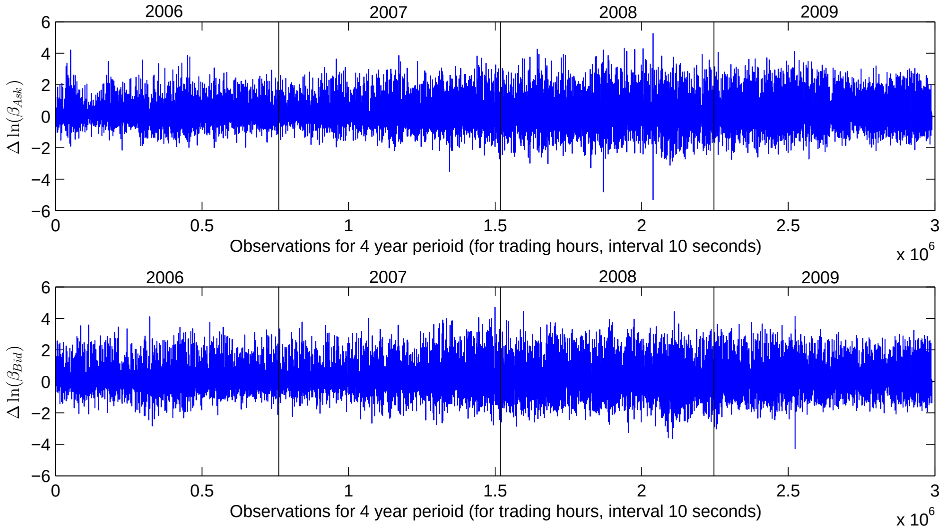

Figure 9: The change in $\ln(\beta)$ for the order book of Nokia between 2006-2009 with 10 second time interval for all trading hours. The black solid lines mark the first observations of each year.

high peaks and long tails. It is again intuitive, that the mean of the changes is zero and they are rather symmetrically distributed around the zero, since we are talking about changes in in the slope of the line, and if the mean of the changes would be something else than zero, the line would essentially be making a round around origin. Based on Figure 10, it may be possible to fit a t-distribution to both $\Delta\beta$ and $\Delta\ln(\beta)$. Fitting the distribution would also become easier if one would leave aside the changes that are zero or nearly zero. That would lower the peak in the distribution and would not necessarily be inconsistent with the intention of the study, since of interest are abnormal changes and if one would leave aside the most normal relatively small changes and would come to the conclusion that some big change is abnormal, it would definitely be abnormal also in the case where one would also consider the relatively small changes. Also changing the time interval to a longer one from the 10 seconds used could cut down the number of relatively small changes, but since the effects we observe in the later chapters occur in short time periods, it is crucial to use time period short enough.

Figures 11 and 12 depict the sample auto-correlation functions and scatter plots for $\Delta\beta$ and $\Delta\ln(\beta)$, respectively. The important thing to notice is that, by using the changes in β and $\ln(\beta)$ instead of plain β and $\ln(\beta)$, we get rid of most of the autocorrelation in the data. According to the sample autocorrelations functions they both seem to be somewhat noteworthy auto-correlated only with the first lag. Also the scatter plots seem to be randomly scattered.

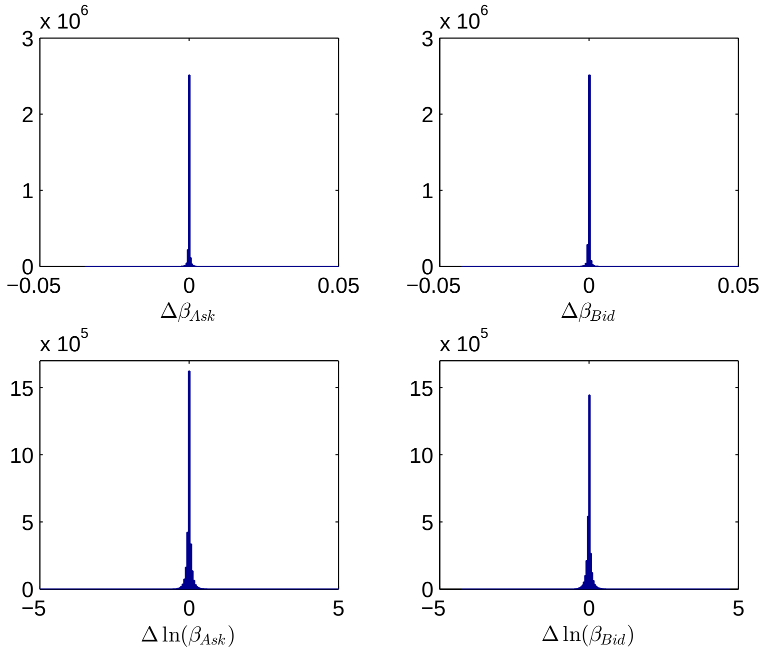

Figure 10: The histogram for changes in β and $\ln(\beta)$ for the order book of Nokia between 2006-2009 with 10 second time interval for all trading hours

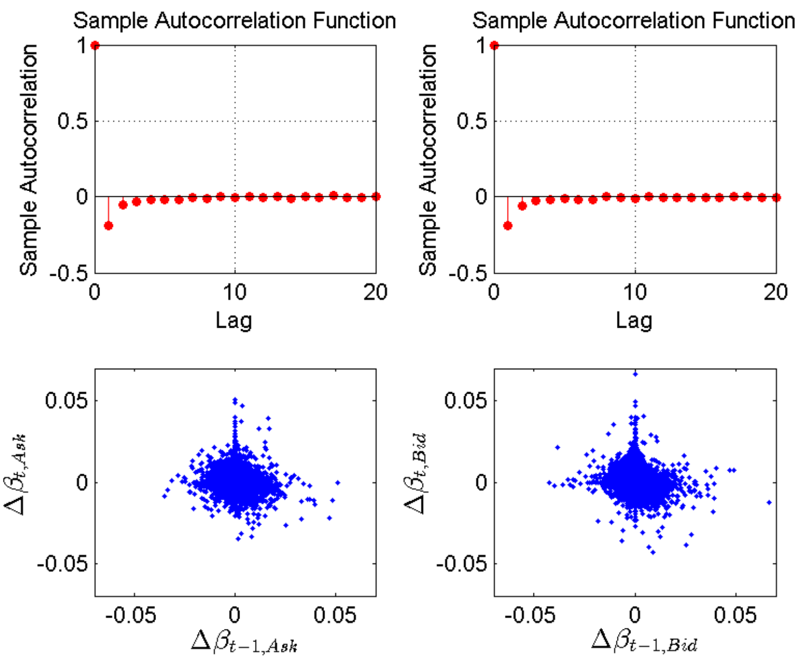

Figure 11: The sample autocorrelation plot and scatter plot for changes in β of the order book of Nokia between 2006-2009 with 10 second time interval for all trading hours

One thing that is especially notable in Figure 12 but can be also somewhat seen in Figure 12, is the cross in the scatter plot. That is at least partly due to the

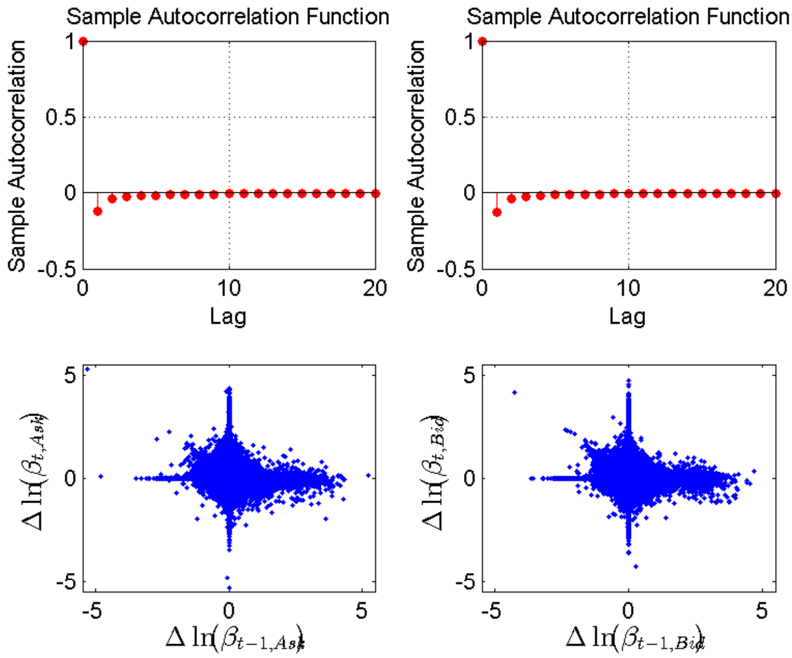

Figure 12: The sample autocorrelation plot and scatter plot for changes in $\ln(\beta)$ of the order book of Nokia between 2006-2009 with 10 second time interval for all trading hours

fact that the last five minutes of the trading day are not continuous trading but pre-close period when no auto matching is done[6]. This means that every day when the pre-close starts, whatever the previous change has been, the next change is zero, which forms the horizontal line. After the pre-close and actually closing the stock exchange the next observations is the first observation of the next trading day, and the change here can again be almost anything after the zero change and this forms the vertical line. We also come back to this in the next subsection which covers the intra-day patterns.

6.7 Intra-day patterns

As noticed already by Malo and Pennanen (2012), there are some intra-day patterns in the liquidity of an order book. Figure 13 shows the intra-day patterns of β and $\ln(\beta)$ for Nokia stock, calculated as mean for each observation moment of a trading day over all the trading days. Like Malo and Pennanen (2012), we also find that the values of β and $\ln(\beta)$ decrease over the trading day, which means that the liquidity of the book increases towards the end of the day. The intra-day patterns cause that if one was to study β and $\ln(\beta)$, one would have to take the intra-day patterns into consideration. In Figure 13 we are also able to observe the effect of halting the

[6]For more information see (NASDAQ OMX Nordic 2011).

continuous trading at 18:25 of local time in the Helsinki stock exchange (NASDAQ OMX Nordic 2011).

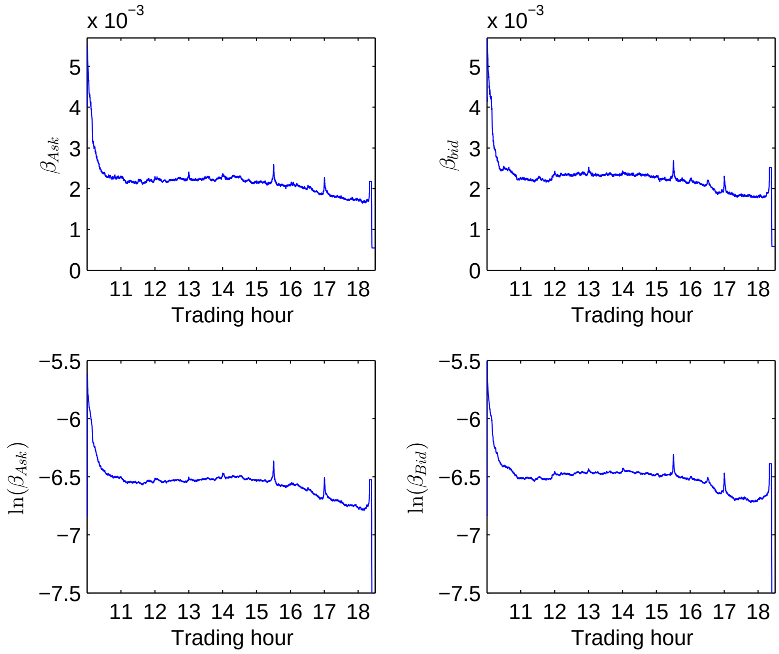

Figure 13: Intra-day patterns of β and $\ln(\beta)$ in Helsinki local time

In Figure 13 we can also distinguish a couple of somewhat notable peaks in β and $\ln(\beta)$. One of them occurs a little bit after 15:30 and an other one around 17 o'clock both Helsinki local time. When dividing the time period into four, the peaks seem to persist. This suggests that the peaks are not due to one single or even couple of abnormal trades. Still the cause of the peaks is hard to tell. Since it is only one stock, it may be possible that the peaks are duo to one major trader's trading habits, for example canceling all the orders before leaving workplace.

Figure 14 shows that, in the case of changes in β and $\ln(\beta)$, there are no considerable intra-day patterns except at the very beginning and the end of the day, which is due to the trading halt before closing the exchange. During the trading hours, there is on average only slight noise to be seen. This means that when studying $\Delta\beta$ and $\Delta \ln(\beta)$, if we cut out the beginnings and the ends of the trading days, it is not that important to take intra-day patterns into consideration.

Furthermore, figures 15 and 16 show that when we remove 60 minutes from the beginning and the end of all the trading days in the data, as suggested in the previous section, the cross in the scatter plots practically disappears (compare to Figures 11 and 12). In fact removing just 15 minutes would be enough to get similar figures, but when removing an hour we should also get otherwise smoother data.

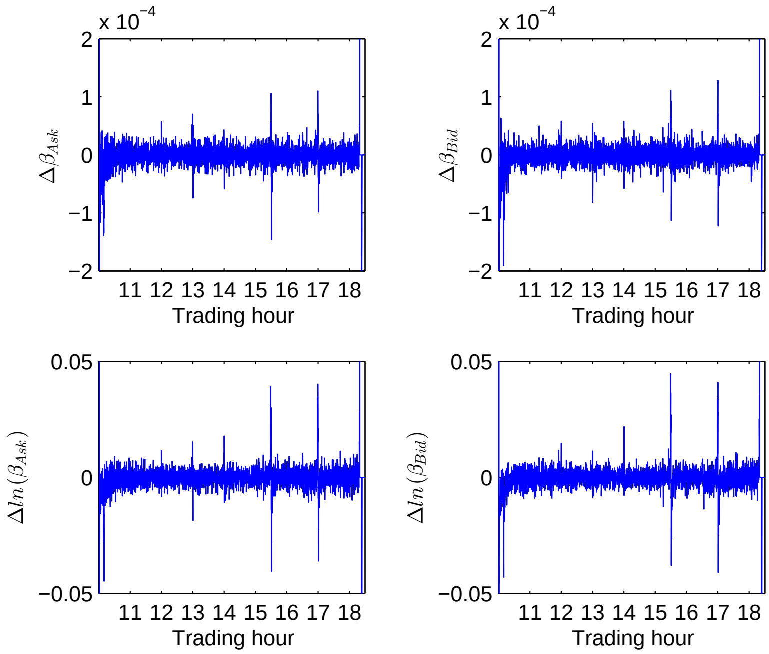

Figure 14: Intra-day patterns of $\Delta\beta$ and $\Delta\ln(\beta)$ in Helsinki local time. The first and last observations of a trading day are not properly observable in the figure due to scaling.

As we noted earlier, the liquidity of the book tends to increase over the day, and in Figure 13 we can see that this trend of decreasing β is especially strong during roughly the first hour of a trading day. This is why the changes in β during roughly the first hour of the trading day are not distributed as evenly with mean of zero as the other observations, but instead tend to be negative (see figure 14).

There are also other trading halts during the sample period[7] which are so far interpreted as zero changes, and by removing them one can in principle further reduce the appearance of the cross in the scatter plots, but one cannot clearly observe that in a figure. But since it is not possible to study the behavior of the limit order book during the trading halts, because no orders can be executed during them, they are ignored in all the calculations that follow. In the data, there are also some other occasions when spread is for some reason momentarily negative or when the best bid and ask offers are at the same price but for some reason automatic order matching does not match the orders (these both are often followed by a trading halt), or one side of the book empty (if there really are no offers on one side or there is some kind of a technical error) which are not taken into account since determining the mid-price and β for those moments would not be reasonable.

[7]For details, see (NASDAQ OMX Nordic 2011).

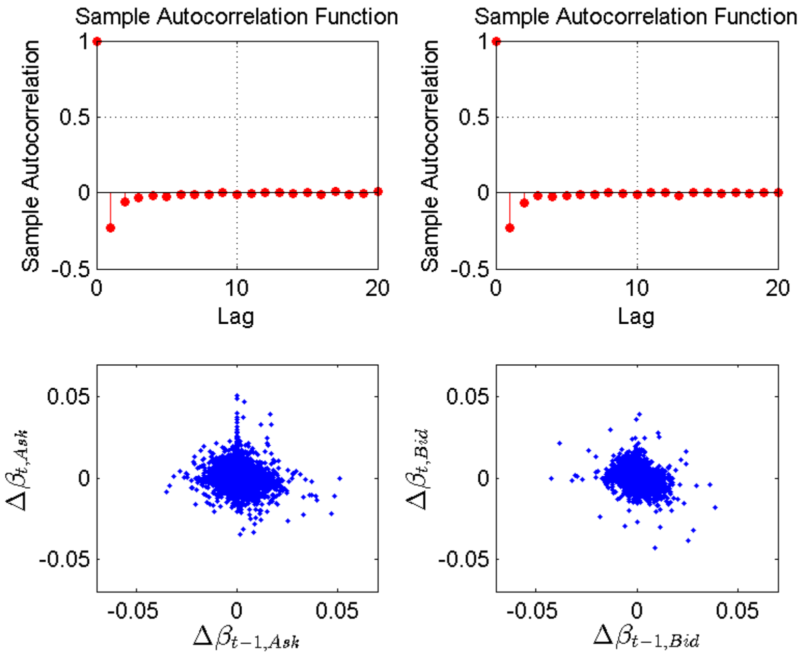

Figure 15: The sample auto-correlation and scatter plot for changes in β of the order book of Nokia with 60 minutes removed from the beginnings and the ends of the days

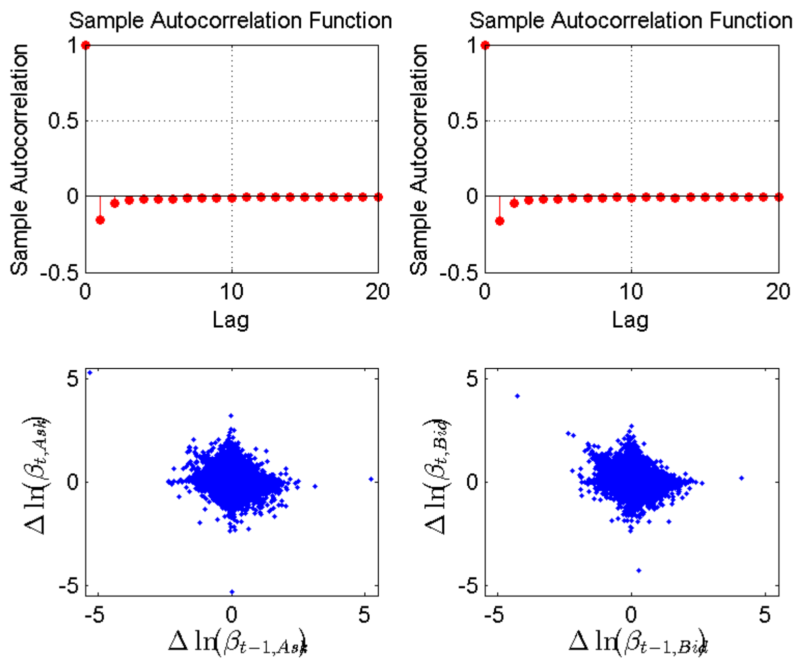

Figure 16: The sample auto-correlation and scatter plot for changes in $\ln(\beta)$ of the order book of Nokia with 60 minutes removed from the beginnings and the ends of the days

7. STUDYING THE BEHAVIOUR OF THE ORDER BOOK AROUND NEWS ANNOUNCEMENTS

7.1 Determining estimation and event window for the study

In a similar manner as in event study analysis used to study abnormal stock returns around e.g. news releases presented by Campbell (1997), this study uses event window and estimation window in order to study the behavior of the limit order book around earnings announcement releases. An event window is a time window in the middle of which the event, in this case the release of earnings announcement, takes place. An estimation window, on the other hand, is a time window before the event during which the behaviour is assumed to be normal and against which the behaviour of the limit order book in the event window is compared. (Campbell 1997) Figure 17 illustrates the estimation window and event window used in this study.

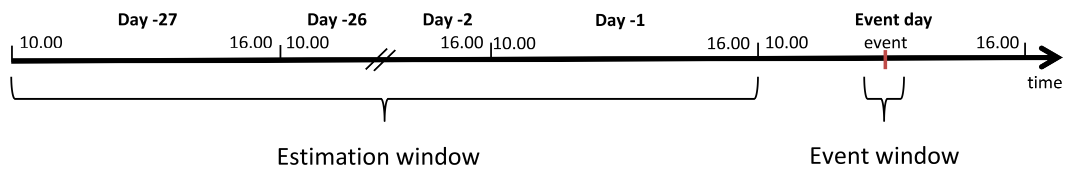

Figure 17: Estimation and event windows in time line (adapted from (Campbell 1997))

Based on the findings about the daily patterns in liquidity reported in Chapter 6.7, this study decides to remove one hour from the beginning and end of each trading day. Furthermore, since the trading day in Copenhagen ends half an hour earlier than in Helsinki and Stockholm, to get similar sample sizes for all exchanges an additional thirty minutes are removed from the ends of the trading days in Helsinki and Stockholm. This means that in practice in the context of this study trading day is considered to be 10:00:00-16:00:00.

Later in this study Kolmogorov-Smirnov statistical test is used to compare changes in β in the event window and the estimation window, and this has an impact on the choice of the lengths of the both windows. Study of Bera et al. (2010) suggests that when comparing distributions of two samples, satisfactory results are obtain when using simple rule of thumb $m = \sqrt{n}$, where m is the size of the first sample, in this case the number of observations in the estimation window, and n is the size of the second sample, in this case the number of observations in the event window.

To get reasonable lengths for both windows, the estimation window is chosen to constitute of twenty minutes before and after the event, meaning that the total length of the event window is 40 minutes. This corresponds to $n = 241$ observations in the event window. This leads to $m = n^2 = 241^2 = 58081$ observations in the estimation window, which corresponds to 26,88 trading days which is rounded to 27 trading days used as the estimation window.

7.2 Filtering the earnings announcements

As specified in Chapter 6.2, there are alltogether 971 earnings announcement releases in the data set used in this study. Nevertheless, there are many releases that take place outside the trading hours or otherwise do not meet the requirements and hence are not applicable. First of all, there needs to be data for 27 days before the day of the event in the data set for the event to be included in the study. Otherwise forming of required estimation window would not be possible.

Moreover, since this study focuses on the immediate reactions around earnings announcement, the event must occur during the trading day in a way that there are enough observations before and after the event. Essentially this means that, since the trading day is restricted to 10:00:00-16:00:00 o'clock and length of the event window, in the middle of which the event takes place, is 40 minutes, the earnings announcement can be included if the release takes place between 10:20:00-15:40:00. The time of the earnings announcement is estimated to be the closest observation moment of the actual time of the release, i.e. the actual time is rounded to the nearest ten seconds. This adds some noise to the results of this study since one cannot be sure if the actual time of the announcement is slightly before or after the estimated time of the announcement, but this should not cause any systematic bias to the results.

Additionally, inclusion of the event requires that there are no trading halts during the event window. This is required because the results would not authentically reflect the behaviour of the traders if the study would include event windows during which the trading would be halted. It should be noted that this leaves out the earnings announcements around which large price fluctuations take place since the large deviations in the price may trigger volatility guard and cause trading halt as discussed in Chapter 5.5.

Furthermore, since the intention is to study liquid stocks, also events during which estimation windows the maximum of value of β on either side of the book exceeds threshold of 0.5 are excluded. This eliminates also the events with extreme values during the estimation window. One could argue that if there are extreme values in the estimation window it is likely that the estimation window does not reflect the normal behaviour of β but there may be some other events occurring during the estimation window. The choice of threshold to be 0.5 leaves out roughly 20% of the events that would otherwise be applicable and the study ends up with 211 earnings announcement releases in the final sample. Table 1 summarizes the number of news in each phase of the filtering. Additionally, the appendix A reports the number of earnings announcements for different companies in the different phases of the filtering.

Table 1: Number of earnings announcement releases in each phase of the filtering. Total news in the sample is the number of earnings announcements published between 1.1.2006-1.1.2010 by the companies included in this study. News with 27 previous days includes the news in the total sample that have 27 previous days in the order book data, i.e. it is possible to form the required estimation window. News released between 10:20:00-15:40:00 on a trading day involve all the earnings announcements that are additionally published during the above-mentioned time of a trading day. No trading halts include the news that in addition do not have any trading halts during the 40 minute time period around the release of the announcement. Liquid news counts all the earnings announcements released that, in addition to requirements mentioned earlier, have relatively liquid estimation windows, i.e. the maximum value of β is less than 0.5, and they constitute the final sample studied.

total news	news with 27 previous days	news published 10:20-15:40	no trading halts	liquid news
971	950	302	255	211

The restrictions concerning the earnings announcements delimit the results to apply only to the earnings announcements that are released during a trading day. One should bear in mind that it is possible that there are for example certain companies that tend to release all the earnings announcements outside trading hours and these results do not apply on those companies. Certainly, as we can see from the appendix A, there are some companies included in this study which have no earnings announcements included in the sample used and the results may not concern those companies. It can also be the case that some types of earnings announcements are released outside the trading hours, for example earnings announcements that contain some surprising new information, and these are not included in the study. Also the liquidity restriction delimits the generalization of the results to stocks that are liquid enough and announcements that do not occur too close to major liquidity reducing events.

7.3 Studying the distribution of the changes in liquidity

7.3.1 Conducting Kolmogorov-Smirnov test to the changes of β

As a starting point this study wants to conclude that the behaviour of the order book around earnings announcements deviates from the normal behaviour. To do this, the distributions of $\Delta\beta$ and $\Delta \ln(\beta)$ in estimation and event windows are compared. As indicated already earlier, the comparison is done by using two sample Kolmogorov-Smirnov test. The two sample Kolmogorov-Smirnow test can be used to show that the two distribution are not independent of each other (Wasserman 2004, p. 241).

The following two hypothesis are set:

- H_0: the distribution of $\Delta\beta$ ($\Delta \ln(\beta)$) is the same in the estimation and event windows
- H_1: the distribution of $\Delta\beta$ ($\Delta \ln(\beta)$) is not the same in the estimation and event windows

The Kolmogorov-Smirnov test is done separately for each event in the sample at 1 % significance level for absolute and relative changes on both sides of the book. Then the percentages of events for which H_0 is rejected for different kinds of changes is calculated. The results are presented in Table 2.

Table 2: The percentage of cases where H_0 is rejected for earnings announcements

$\Delta\beta_{Ask}$	$\Delta\beta_{Bid}$	$\Delta \ln(\beta_{Ask})$	$\Delta \ln(\beta_{Ask})$
91.0 %	89.6 %	90.0 %	86.3 %

Table 2 shows that for both absolute and relative changes of β on both sides of the book H_0 is rejected in roughly 90 % of the events. The results are similar when using 5 % significance level, removing only 30 minutes from the beginning and end of the trading day, using one or two hour event window or leaving one day between the event day and estimation window. One would not expect to get rejection in 100 % of the cases since the earnings announcement data is not perfect in the sense that it can contain also events that actually are not earnings announcement releases.

In order to be able to compare the results reported in Table 2, a sample of random moments is chosen. The random sample consists of an equal amount of random moments during the four year sample period as there is in the event sample. Moreover, the random moments are chosen with same proportion for different companies as there are in the event sample. Table 3 gives the results for the random sample.

Table 3: The percentage of cases where H_0 is rejected for random moments

$\Delta\beta_{Ask}$	$\Delta\beta_{Bid}$	$\Delta\ln(\beta_{Ask})$	$\Delta\ln(\beta_{Ask})$
22.7 %	30.3 %	19.9 %	24.2 %

In Table 3 one can see that the rejection percentage of H_0 fluctuates between 20 % and 30 %. We get similar results also with other randomly chosen moments. One should also bear in mind that 0 % is not expected since the moments are chosen randomly and hence they can contain even earnings announcement releases or other major events. Additionally, it is possible that the distribution changes in time and hence H_0 gets rejected. Irregardless, the percentages seem to be significantly lower for randomly chosen moments than the results for actual earnings announcements.

7.3.2 Analyzing the significance of differences in the distributions

To show that the differences in percentage rates of rejecting the hypothesis that the distribution of absolute and relative changes in β are the same in the estimation and event windows, Pearson's χ^2 test is conducted. Pearson's χ^2 is used to test whether two random variables are dependent (Wasserman 2004, pp. 239-242). In this case the first variable is if H_0 gets rejected or not. We mark this with H_0 and it gets the value 1 if H_0 is rejected. The other variable is event and it gets the value 1 if the event is one of the earnings announcements of the sample of this study and 0 if it is a random moment. The earnings announcements and random moments used in the previous section are used as the sample when conducting the Pearson's χ^2 test.

The results of the Pearson's χ^2 test are reported in the appendix B. For absolute and relative changes on both sides of the book the p-value $p < 0.000001$ indicates very strong evidence (Wasserman 2004, p. 157) that rejecting the hypothesis that the distribution of changes in β are different in the event and estimation windows is associated with earnings announcement release, i.e. abnormal behaviour of liquidity of an order book is related to earnings announcement releases. Even though based on Pearson's χ^2 test one cannot deduce that the other variable causes the other one to be something specific, but only that they are associated (Wasserman 2004, p. 242), in this case we can conclude that the release of the earnings announcement causes the abnormal behaviour of β since the release of an announcement is scheduled and regulated so an earnings announcement cannot be released as a response to abnormal behaviour of the order book.

As showed in the Chapter 6.6, there is still some slight first lag autocorrelation in the changes of β. Therefore a simple AR(1)-model is fitted to the changes in β to see if removing the autocorrelation would have an impact on the results. Fitting the AR(1)-model is shortly explained in the appendix C. When using the residuals of the AR(1)-model similar results as when using just the unadjusted changes are obtained. The p-values remain at the same level, even though it seem that, in the case of random events, H_0 gets rejected slightly more often. On the other hand since, as β, also the changes in β are so fundamentally dependent on the preceding values[1] that it may not even be possible to get truly independent values. When plotting an autocorrelation plot for the values of the AR-residuals for 11 Nokia's earnings announcements (figures not reported in this study) there seem to exist some mainly negative autocorrelation beyond the first lag. However, the sample size is notably smaller than what is studied in the Chapter 6.6.

7.4 Studying the behaviour of liquidity

7.4.1 Method used to aggregate over the events

In the previous subsection we observed the relatively intuitive finding that the behavior of the limit order book is not normal around earnings announcement releases but abnormal changes in the liquidity are observed. However, more of an interest is how the liquidity develops around earnings announcements. To address this question the values of β are aggregated over all the events in the sample. The same length of the estimation window and event window is used as in the previous subsection when applying the Kolmogorov-Smirnov test.

To study the level of the liquidity absolute values of β rather than changes in β are used, and also not $\ln(\beta)$ since absolute values are easier to interpret. But as we noticed in the Chapter 6.7, there are notable intra-day patterns in the liquidity in the course of a day that one has to take into consideration. To do this, for each event in the sample a set of dummy variables, γs, is estimated. γ is estimated for each observation moment of the six-hour part of a trading day from the observations of

[1]The changes in β cannot constantly be positive or negative since otherwise the fitted line would essentially be making a round.

the estimation window. γs are calculated as a mean value of all[2] the observations at a specific moment of the day for each event separately. We get the de-seasonalized value for β at a specific moment t of the day[3] by subtracting the dummy variable of that time γ_t of the observation. Additionally, since many of the announcements happen around noon, we can artificially convert all the events to happen at 12:00:00 o'clock by adding the dummy variable of 12:00:00 $\gamma_{12:00:00}$ to the result of the subtraction. So we get the de-seasonalized 12 o'clock values for each event i at time t as

$$\beta_{i,t}^{DS} = \beta_{i,t} - \gamma_{i,t} + \gamma_{i,12:00:00}$$

All the observations in all the estimation windows and event windows are de-seasonalized and moved to 12 o'clock in this manner.

To aggregate over all the events, for each observation moment t in both estimation window and event window the mean β of that time, $\overline{\beta_t}$, is calculated as a mean of $\beta_{i,t}^{DS}$s over all i events[4]. So the mean observation for each observation moment is

$$\overline{\beta_t} = \frac{1}{N} \sum_{i=1}^{N} \beta_{i,t}^{DS},$$

where N is the number of events in the sample. The problem in taking the average is that less liquid stocks with bigger values of β get more weight than the more liquid ones, but our limitation to take into account only events where the maximum value of β in the estimation window is less than 0.5, discussed in subsection 7.2, strives to reduce the bias caused by this.

7.4.2 Findings about the level of liquidity

To get an idea of the level of β around earnings announcements and the evolution of liquidity in time, the study plots the average β over all the announcements around the time of the announcement. Figure 18 presents the mean of β, $\overline{\beta}$, for the ask and bid sides of the order book over all events. We see that during the 20 minute time period before the event, the liquidity remains rather stable. But notably, liquidity during that period is much lower than in the estimation window on average; on the ask side, $\overline{\beta}$ is around the maximum value of the estimation window and, on the bid side, even above the maximum of the estimation window.

In figure 18 we can also see that right after the announcement there is a notable

[2] Observations during trading halts are ignored.

[3] t having values every ten seconds between 10:00:00 - 16:00:00.

[4] Again, observations during trading halts are ignored.

peak in $\overline{\beta}$ on both sides of the book. But after five minutes $\overline{\beta}$ has declined roughly to the level of the maximum $\overline{\beta}$ of the estimation window on both sides of the book and 20 minutes after the event, i.e. at the end of the event window, $\overline{\beta}$ has recovered to the average level of the estimation window or even slightly below that on the ask side. Overall, Figure 18 shows the pattern observed by Malo and Pennanen (2012) that liquidity on bid side is lower than liquidity on the ask side.

Earnings announcements bring new information to the market, and hence one could assume that the information can be positive or negative in the sense that, as a consequence of the announcement, the price either rises or falls. Now the intention is to study if the nature of the announcement has an impact on the behaviour of the order book around earnings announcements. Therefore the events are categorized based on whether the mid-price at the observation moment preceding the observation moment of the event is lower or higher than the mid-price at the last observation moment of the event window, i.e. 20 minutes after the release of the announcement. If the mid-price right before the event is lower than the mid-price at the end of the event window, the event has led to a price increase. Thus, we say that the event was positive and, vice versa, if the price has decreased, we say that the event was negative.

When dividing the events in the sample using the method described above, we end up with 107 positive events and 92 negative events. So both sample sizes remain fairly robust and there is roughly the same amount of both types of events. However, there are alltogether 12 events that are neutral, meaning that the mid-price right before the event is the same as at the end of the event window. The distribution of the different event types over the companies is reported in Appendix A. With larger sample sizes, it would be reasonable to actually divide the sample at least in three, positive negative and neutral, for example in a way that if the absolute value of the change has been less than a specific percentage, the event is classified as neutral. Since the sample size of neutral events in our study is so small, we do not report the results concerning them in such detail as positive and negative events[5].

[5]Intuitively, it seems highly unlikely that the price remains unchanged if the stock is liquid and regularly traded, assuming that there really is a release of an earnings announcement. However, it can be the case that the earnings announcement does not contain any new information that would affect the valuations of the underlying firm. In the case of this study, the news data is not perfect in the sense that one could be sure that there actually happens a release of earnings announcement at the moment one assumes it happens. We can actually notice that half of the neutral announcements are not releases of earnings announcements, but usually announcements of the timings of the future earnings announcements releases. Notably, all except one of the neutral events concern stocks traded in Stockholm Exchange, one is traded in Copenhagen Exchange and all of the announcements are released during the first two years of the sample period, i.e. during 2006-2007.

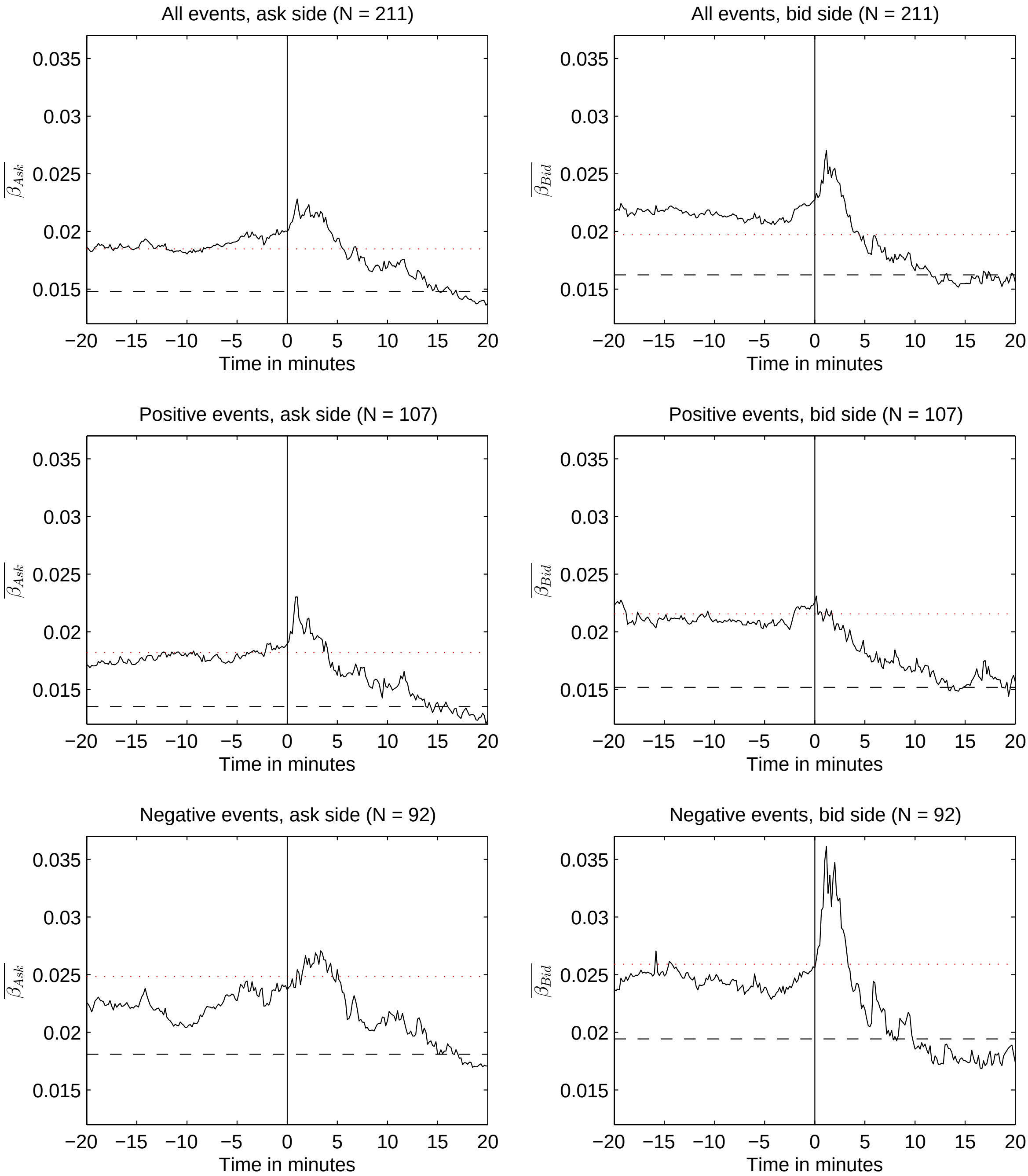

Figure 18: $\overline{\beta}$ around earnings announcements for all events, positive events and negative events. Black solid line corresponds to $\overline{\beta}$, black dashed line corresponds to the average of $\overline{\beta}$ in the estimation window and red dotted line corresponds to the maximum value of $\overline{\beta}$ in the estimation window. The black line at time zero corresponds to the time of the earnings announcement.

Figure 18 shows that the evolution of the liquidity before positive events is quite similar when compared to all events, $\overline{\beta}$ is rather stable but slightly below the maximum value of $\overline{\beta}$ in estimation window. Nevertheless, the peak right after the event observed when studying all the events appears only on the ask side when considering only the positive events. On the bid side, right after the event, $\overline{\beta}$ starts to decrease quite steadily from the level of the maximum $\overline{\beta}$ in the estimation window. As in the case of all events, by the end of the event window $\overline{\beta}$ in both sides has reached the level of average $\overline{\beta}$ in the estimation window.

In Figure 18, we can also observe that the behaviour of the liquidity before negative announcements seems to be slightly more different when compared to all events. On both sides $\overline{\beta}$ is notably lower than the maximum value of $\overline{\beta}$ in the estimation window and it is not as stable[6]. In contrast to the case of positive events, with negative events there appears an remarkably high peak of $\overline{\beta}$ on the bid side, whereas on the ask side it is questionable whether there exists any peak. Irregardless, by the end of the estimation window $\overline{\beta}$ decreases slightly below the average level of $\overline{\beta}$ in the estimation window.[7]

To verify that the findings are not solely caused by single events, we can also plot the standard deviation of β around the events (see Figure 27 in Appendix D). For positive events on the bid side the standard deviation is rather stable and only slightly above the average standard deviation in the estimation window and well below the maximum standard deviation in the estimation window, whereas on the ask side the standard deviation is also otherwise quite stable and close the the average of the estimation window, but there is a small peak after the event, still being all the time well below the maximum value of the estimation window. With all events and negative events the shape of the standard deviation curve is similar, but the level is lower with all events. In the case of all events and negative events, the standard deviation is mainly between the average value and the maximum value of the estimation window, with the exception a peak on each side of the book after the event. On the bid side the peak is notably high. The findings of studying the standard deviation around event times are interpreted so that the findings concerning the evolution of liquidity are not mainly driven by a few unusual events, except that the outstandingly high peak of $\overline{\beta}$ after the event in the case of negative events may be

[6]However, the maximum value in the estimation window is just one single high value and hence may not be that representative for the estimation window as whole, and also the reduction in the sample size is likely to add noise to the observations.

[7]For the neutral events the evolution of liquidity in the event window is quite different. $\overline{\beta}$ is well below the maximum value of the estimation window for the whole time and at least on ask side distinguishing the event time in Figure seems impossible. But making any conclusions based on those findings is unfeasible since the sample size is so small and half of the events are not even publications of earnings announcement.

reinforced by a few extreme events.

7.4.3 Mid-price and spread

It is also interesting to study how the mid-price and spread develop around releases of earnings announcements on average. However, to be able to sensibly aggregate over the different events, some relative measure is needed instead of plain mid-price. This study chooses to calculate the average log-return on mid-price of the first observation moment of the event window for all the moments in the event window. It is marked with $\overline{m}$ and calculated for each observation moment t as

$$\overline{m_t} = \frac{1}{N}\sum_{i=1}^{N} \ln\left(\frac{\text{mid-price}_{i,t}}{\text{mid-price}_{i,0}}\right),$$

where N is the number of events.

Figure 19 presents the evolution of $\overline{m}$ around earnings announcements alongside with $\overline{\beta}$ for the ask and bid sides for positive and negative events. We see that before the announcement $\overline{m}$ stays steadily as zero, meaning that the mid-price does not change on average during the 20 minute time window before the announcement. But immediately after the event $\overline{m}$ starts to rise in the case of positive events and fall in the case of negative events. The shape of the curve is exponential on both sides meaning that right after the the change is more rapid and towards the end of the event window $\overline{m}$ starts to stabilize. The evolution of $\overline{m}$ seems to be symmetrical in the case of positive and negative events, and at the end of the event window the average log-return on mid-price has been roughly 2,6 % for positive events and respectively -2,6 % for negative events.

Since spread is also a common measure of liquidity (see Chapter 3), it is interesting to see how it develops around earnings announcements. To be able to meaningfully aggregate spread over different events and companies, again a relative measure is needed instead of studying plain spread. This study decides to use proportional spread, i.e. divide the spread of a specific observation moment with the mid-price of the same moment to get a relative measure of spread (Roll and Subrahmanyam 2010) and then take the average over these over the events. For observation moment t this is marked with $\overline{\kappa_t}$ and is calculated as

$$\overline{\kappa_t} = \frac{1}{N}\sum_{i=1}^{N} \frac{\text{spread}_{i,t}}{\text{mid-price}_{i,t}},$$

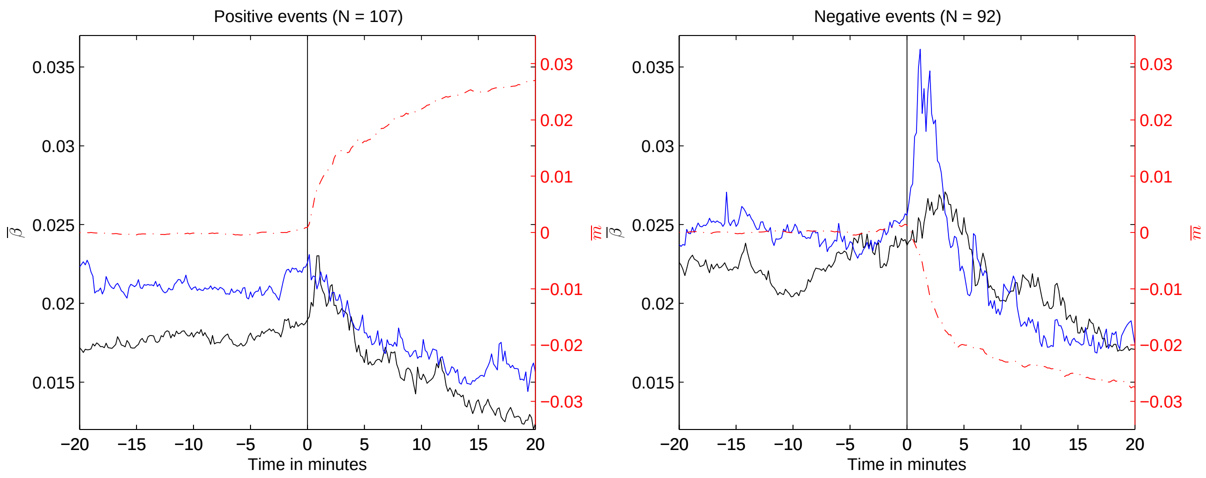

Figure 19: $\overline{m}$ around earnings announcements. The red dash-dot line corresponds to $\overline{m}$ with scale on the right hand side with red and the black solid line corresponds to $\overline{\beta}$ on the ask side and the blue solid line corresponds to $\overline{\beta}$ on the bid side, both with scale on the left side marked with black. The black line at time zero corresponds to the time of the earnings announcement.

where N is the number of events. Figure 20 shows $\overline{\kappa}$ around releases of earnings announcements separately for all events, positive events and negative events with $\overline{m}$.

In figure 20 we see that before the event $\overline{\kappa}$ is a bit over the average level of the estimation window but well below the maximum value of $\overline{\kappa}$ in the estimation window until, approximately five minutes before the event, there appears to be a slight increase in the level of $\overline{\kappa}$. Immediately after the event there is a notable peak in $\overline{\kappa}$ in the case of positive events, but for the negative events the reaction seems to be slightly slower. Still, in the both cases $\overline{\kappa}$ reaches the same level. This shows in the case of all events as a wider peak as with just positive or negative events. The slightly faster reaction in the case of positive events also shows in the case of all events, where $\overline{m}$ seems to be somewhat stable during the whole event window, but when taking a closer look one can see that right after the event there is a slight peak first upwards and then a base downwards before stabilizing again. In all cases, after the peak $\overline{\kappa}$ starts to decline, but notably, in all the cases $\overline{\kappa}$ does not return to the same level as before the event, near the average of $\overline{\kappa}$ in estimation window, but instead seems to somewhat stabilize at a bit higher level. By comparing the different cases one can also notice that the maximum value of $\overline{\kappa}$ in estimation window is much higher for negative events than it is for all events or positive events. However, since the average values of $\overline{\kappa}$ are roughly the same it is likely that the difference in the maximum is due to one extreme observation rather than telling about major differences.

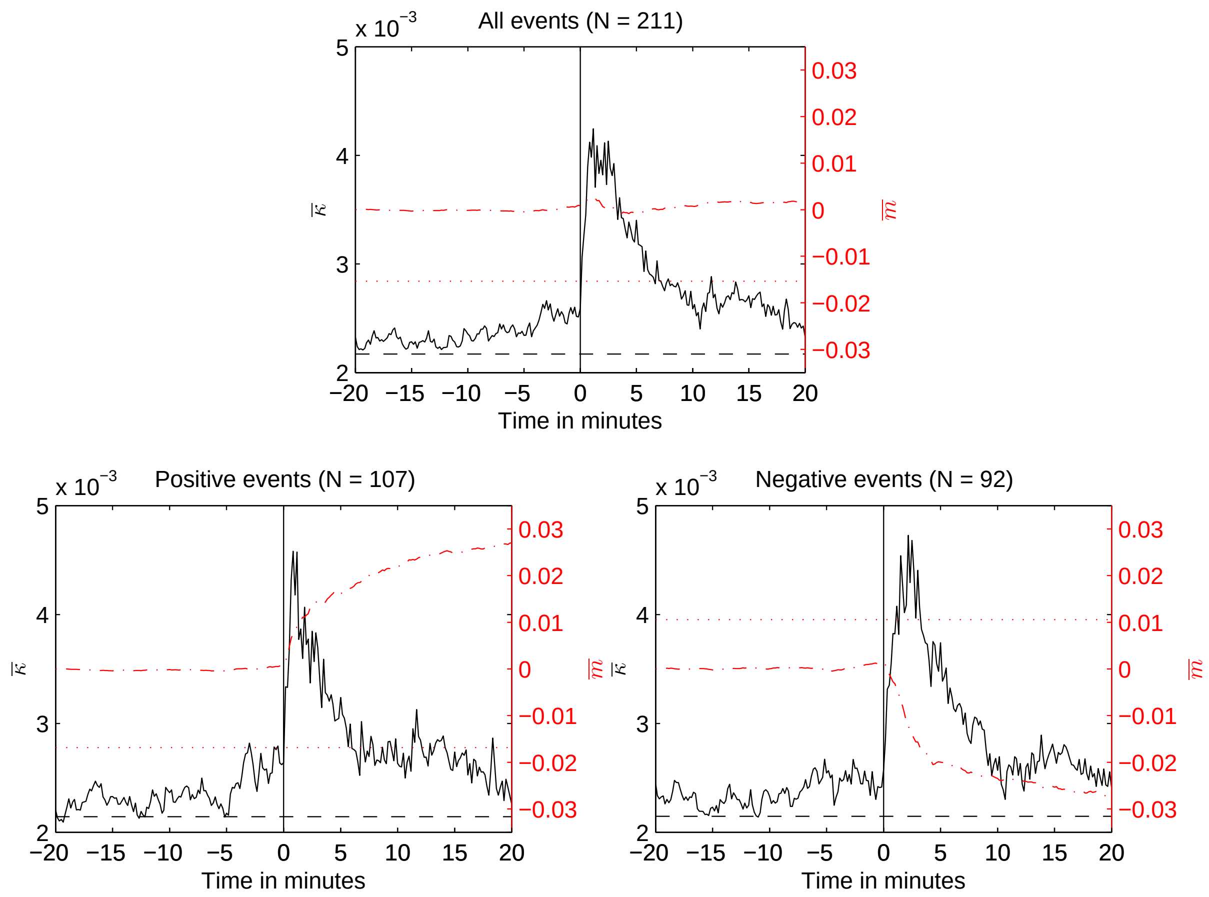

Figure 20: $\overline{\kappa}$ around earnings announcements.The black solid line corresponds to $\overline{\kappa}$ with scale on the left hand side and the red dash-dot line corresponds to $\overline{m}$ with scale on the right hand side with red. Black dashed line corresponds to the average of $\overline{\kappa}$ in estimation window and red dotted line corresponds to the maximum value of $\overline{\kappa}$ in the estimation window. The black line at time zero corresponds to the time of the earnings announcement.

7.4.4 Average changes in liquidity

To study the relative changes in liquidity around earnings announcements more closely than in Chapter 7.3, this study aggregates also $\Delta\ln(\beta)$ as described in Chapter 7.4.1 to get values for $\overline{\Delta\ln(\beta)}$ in estimation and event windows. Additionally, standardizing of $\overline{\Delta\ln(\beta)}$ in both windows is done. The standardized values are marked with $\overline{\Delta\ln(\beta)}^{ST}$ an they are calculated for each observation moment t in estimation window and event window as

$$\overline{\Delta\ln(\beta)}_t^{ST} = \frac{\overline{\Delta\ln(\beta)}_t - \mu_{est}}{\sigma_{est}},$$

where μ_{est} is the mean value of $\overline{\Delta\ln(\beta)}$s in the estimation window and σ_{est} is the standard deviation of the same values.

Histograms in Figure 21 show that standardized values of $\overline{\Delta\ln(\beta)}$ are rather symmetrically distributed and actually nearly normally distributed. To estimate what are normal values of $\overline{\Delta\ln(\beta)}^{ST}$, the study estimates 99% confidence interval from the empirical distribution of $\overline{\Delta\ln(\beta)}^{ST}$ in the estimation window. 99% of the observations of $\overline{\Delta\ln(\beta)}^{ST}$ in the estimation window are inside these limits. The limits are plotted in Figure 22 with the observations of $\overline{\Delta\ln(\beta)}^{ST}$ in the event window for all events, positive events and negative events for both sides of the order book separately.

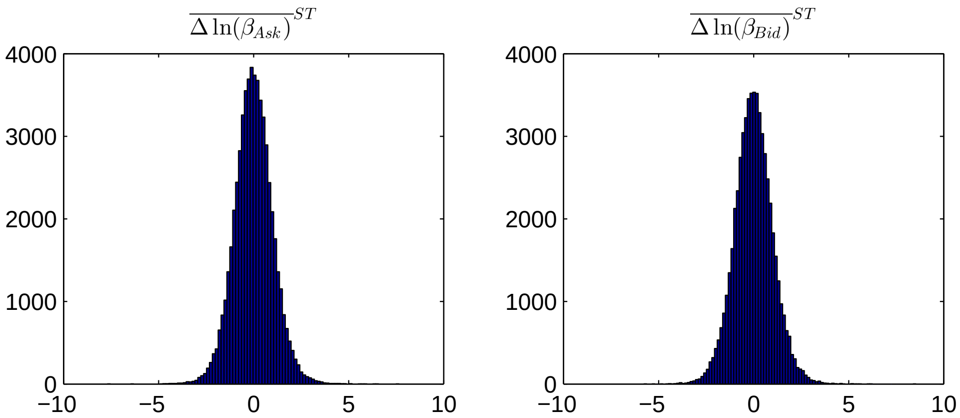

Figure 21: Distribution of $\overline{\Delta\ln(\beta)}^{ST}$ in the estimation window

From Figure 22 we see that, for all events and positive events as well as for negative events, $\overline{\Delta\ln(\beta)}^{ST}$ stays rather steadily inside the confidence interval[8] for the 20 minutes time interval before the announcement. However, after the event things change. For all events we can see that there is a high peak in $\overline{\Delta\ln(\beta)}^{ST}$ right after the event for the ask side, for the bid side the volatility of $\overline{\Delta\ln(\beta)}^{ST}$ increases right after the event, but there appears no such immediate positive peak or negative base. On the ask side after a positive peak and on the bid side after a couple of rather modest peaks, $\overline{\Delta\ln(\beta)}^{ST}$ falls to rather low levels and starts to climb somewhat slowly to the normal level, being during the last ten minutes of the event window at rather normal level but with higher variation than before the event.

For positive events the behaviour of $\overline{\Delta\ln(\beta)}^{ST}$ is rather similar when compared to all events, except that on the bid side there is a low base right after the event. In the case of negative events again the evolution of $\overline{\Delta\ln(\beta)}^{ST}$ is more or less similar to the case of all events except during the roughly five minute time period right after the event. On the ask side, even though the variance of $\overline{\Delta\ln(\beta)}^{ST}$ increases right after

[8]There are few exceptions when the value of $\overline{\Delta\ln(\beta)}^{ST}$ slightly exceeds the confidence interval but it is normal that some values exceed the interval since there are 120 observation before the event and on average one observation out of hundred exceeds the 99% confidence intervals.

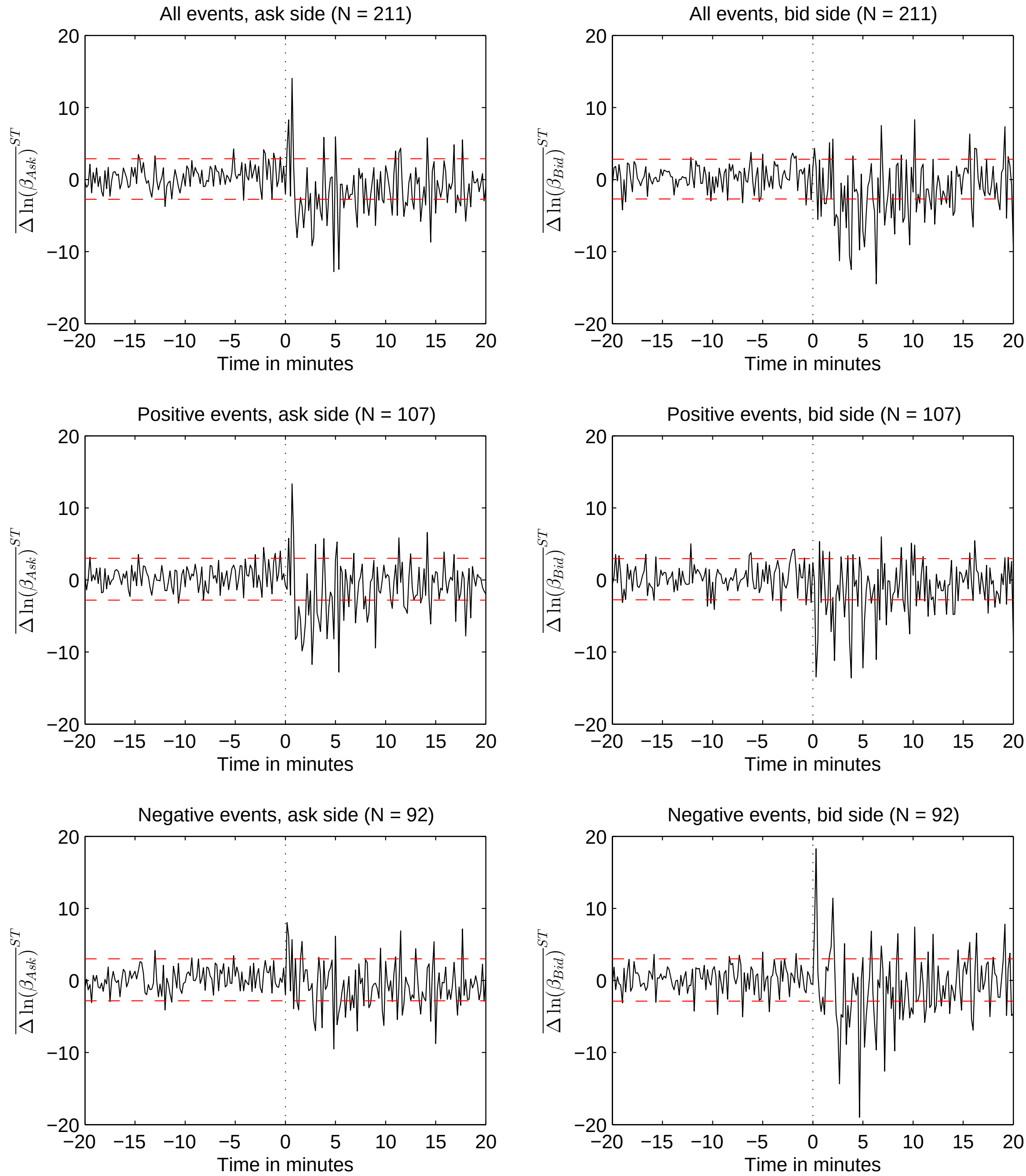

Figure 22: $\overline{\Delta \ln(\beta)}^{ST}$ around earnings announcements for all events, positive events and negative events. The black solid line corresponds to $\overline{\Delta \ln(\beta)}^{ST}$ and the red dashed lines represent the 99% confidence interval estimated from the empirical distribution of $\overline{\Delta \ln(\beta)}^{ST}$ in the estimation window. The black dotted line at time zero corresponds to the time of the earnings announcement.

the event, $\overline{\Delta \ln(\beta)}^{ST}$ remains at rather normal levels. But on the contrary, on the bid side there is extremely high positive peak right after the event, followed by an other quite high positive peak and which is then followed by a rather low negative base and then extremely low negative base appears.

8. DISCUSSION

8.1 Discussion of the findings

The statistical tests conducted at the beginning of the previous chapter show that the behaviour of a limit order book is abnormal around earnings announcement releases. The findings reported later in that chapter add to these findings by indicating that the changes in the liquidity are abnormally large during the 20 minute period after the release. This is rather intuitive since one could expect that an earnings announcement may contain some new information concerning the earning power of the company, which in turn may have an impact on the fundamental value of the firm and hence the stock price. As a result, the stock price changes and the order book has to adjust to the new price. This can also be assumed to lead to changes in liquidity when the order book shifts to a new place, and there may be also some uncertainty about the new value that can cause illiquidity. As the study of Sandås (2001) suggests that there may be a delay between the release of new information and adjustment of the limit order book, based on this study it seems that the changes in the order book need some time.

The results in the previous chapter also show that the liquidity during the 20 minute time window before the release of an earnings announcement is at relatively low level when measured with β. This would be consistent with the findings of Roll and Subrahmanyam (2010) as they find that illiquidity is greater prior to earnings announcements compared to other times using spread based measures. However, when measured with spread, this study shows that the liquidity is at rather normal level prior to the earnings announcements until slightly lowering approximately 5 minutes before the earnings announcement. Because earnings announcement releases are expected events, it is likely that many orders have been canceled to avoid adverse selection problem and this may be seen as the higher value of β, i.e. lower liquidity. The fact that the level of liquidity measured with β is stable before the announcement could indicate that there are not many trades taking place before the announcement. This could indicate the uncertainty related to the new information, which may lead to shutting down the whole market before the announcement as noted by Linnainmaa (2005).

Since Linnainmaa (2005) reports in his study that institutional investors supply liquidity before earnings announcements, one may interpret the findings of this study so that many individual investors have canceled their orders prior to the announcement, probably more than 20 minutes before the announcement, and the remainder of liquidity that is available is mainly supplied by institutions. This would be consistent with the view that individual investors are uninformed and hence face the adverse selection problem, whereas institutional investors are informed and do not have to worry about getting picked-off (Bloomfield et al. 2005). The finding that also the mid-price seems to stay rather stable on average during the 20 minutes window before the event supports the idea that it may be the case that there is not much trading taking place before the release but investors rather wait for the new information. Over all the findings do not seem to give any evidence about insider trading during the 20 minute time period before earnings announcement.

The negative shock in the liquidity right after the event indicates that orders either get canceled or executed, but based on solely this study we cannot say which one happens. As Linnainmaa (2005) found in his study that after the earnings announcement institutions submit large amounts of market orders taking the liquidity available, we could interpret the findings of this study so that the peak is mainly caused by institution's market orders executing against the stale limit orders of individual investors that were not canceled before the event. It can also be the case that, in addition to submitting market orders, the institutional investors quickly cancel their stale limit orders, which further weakens the liquidity. Regardless, this would mean that the institutions have quickly interpreted the information content of the earnings announcement since otherwise they would not be able to react fast.

The results in the previous chapter also show that the mid-price starts to move immediately after the announcement. Because Mu et al. (2010) conclude that the role of institutional investors in driving large price fluctuations is more important than the role of individuals, it would seem reasonable also from this perspective that institutions are the active part trading after earnings announcements. Since the mid-price seems to somewhat stabilize by the end of the 20 minute window after the announcement and also the overall liquidity measured with β has returned to normal level, one could interpret this to mean that in 20 minutes most of the investors have interpreted the announcement and somewhat agree about the new price, since the book has returned to more or less normal level. The change in the mid-price is fastest right after the event probably because the ones who are able to quickly interpret the announcement want to take advantage of the information before the stale orders get canceled or someone else executes them. The overreaction related to intraday price changes observed by Mu et al. (2010) does not seem to be observable in this study.

In the previous chapter we also observed that when dividing the events into positive and negative events, the shock in the liquidity measured with β after the announcement appears only on the ask side in the case of positive events and in the case of negative events mainly on the bid side. β on both sides of the book depends on the mid-price by definition, since the line of which slope β is, is set to intersect in origin, and the relative location of all the price levels depends on the mid-price. Essentially one could think β to be related with $\hat{\beta}$, which would be the slope of the original order book without conversion of price to r and quantity to h. If mid-price changes due to changes in the submitted orders on one side of the book and the other side of the book remains unchanged, the change in the mid-price causes also a change in $\hat{\beta}$ of the otherwise unchanged side. So the observation that the liquidity on the opposite side of the price reaction does not change may indicate the after the announcement, orders on both sides of the book change. In the case of a positive event, ask orders get executed causing the liquidity on the ask side weaken. But it seems that since the liquidity on the bid side is not weakening, there should be limit orders submitted on the bid side right after the event. The opposite should hold in the case of negative events. But the finding that the spread widens may not be supporting this theory. It may be the case that mid-price changes change β so little that it is not observable in the figures of the previous chapter.

Additionally, in the case of positive and negative events, it seems that the reaction in the case of positive events is slightly faster than in the case of negative events. One interpretation for this would be that, in the case of negative events, to be able to benefit one must sell stocks and if one does not own the stock it must be shorted. But since short selling is restricted and there are additional costs related to it, it may be the case that before shorting the investors take an additional minute to interpret the news before actually shorting the stock to make sure that their interpretation is right.

The figures in the previous chapter also show that spread gives a somewhat different idea of the level of liquidity around earnings announcements than β. When measured with β, the liquidity is lower than on average before the announcement but 20 minutes after the announcement β has returned to regular level. In contrast to this, when measured with spread, the liquidity is at rather normal level before the announcement, but at the end of the event window, i.e. 20 minutes after the event, the liquidity is at lower level. This indicates that neither β nor spread tells the whole truth about the liquidity indicating that even though based on β it seems that 20 minutes after the event most of the market participants have interpreted the announcement and agree on the price, in reality this may not be the case. However, the slightly slower reaction in the case of negative events is present also in the figures with spread. On the perspective of individual trades this means that the liquidity for large trades is improved by a release of the earnings announcement as β, i.e. illiquidity, is higher before the announcement and returns to normal level rather soon after the event. However, for small trades taking place only at the best price levels the opposite holds: the liquidity measured with spread is lower prior to the announcement compared to 20 minutes after the announcement.

As noted in Chapter 4.2, the literature proposes two possible outcomes regarding news announcements and information asymmetries. According to the first one, news announcements decrease information asymmetries while the second one actually predicts that news announcements increase information asymmetries and give advantage to those who are able to interpret the piece of news quickly. (Engelberg et al. 2012) For example Gajewski (1999) discovers that information asymmetries increase around earnings announcements and also the study of Engelberg et al. (2012) finds support on the second view. Based on findings of this study and related literature discussed earlier in this Chapter, it seem that the immediate impact of the earnings announcement release on the information asymmetry is that information asymmetries increase, since there exists a liquidity shock right after the event suggesting that traders do not agree about the price and some uncertainties exist which lead to uninformed investors canceling the orders to avoid getting picked-off. Institutions may be faster interpreting the information and hence taking advantage of the stale limit orders of uninformed traders. This would support the second view. However, the increases in information asymmetries may not be long lived since the findings about the level of β would indicate that 20 minutes after the announcement there does not exist large information asymmetries in the market. Hence, when considering 20 minute time interval, the earnings announcement would have actually decreased information asymmetries supporting the first view proposed in the literature.

In the figures of the previous chapter we also observe pattern reported also by Malo and Pennanen (2012) that liquidity on the bid side is lower than liquidity on the ask side. Malo and Pennanen (2012) give two explanations for this. First, it may be due to the fact that market crashes are more common than sudden upward movements and traders on the bid side are exposed to crashes. The other explanation is that, since the sample period used by Malo and Pennanen (2012) was short (3 months), the tendency may be related to market conditions. But since the phenomena is observed also in this study with 4 year sample period it seems unlikely that the phenomena is caused by market conditions.

8.2 The assessment and limitations of the study

This study manages to answer the research question concerning the evolution of liquidity around earnings announcements rather well. The study also proposes an answer to the question related to the information asymmetries and behaviour of traders, but the answer is somewhat speculative. Overall, the study may provide some new insights concerning the behaviour of limit order book in situations where new information comes to the market. Moreover, the results may be applicable also to other types of news announcements that are prescheduled and provide the investors with new information about a specific company, but most likely not to corporate announcements that are not scheduled but come as a surprise.

One should also bear in mind that the findings concern only liquid and frequently traded stocks. Moreover, the final sample studied is less than 75 stocks since there are companies that consistently release the earnings announcements outside the trading hours. This leads to another limitation: the results only concern earnings announcements released during the trading day. It may be the case that some types of earnings announcements, e.g. ones that contain highly surprising information, are usually released outside regular trading hours and hence the results are not applicable to those. The liquidity constrain of the estimation window also limits the earnings announcements preceded by liquidity shocks out side the scope of this study. Additionally, these results concern stocks traded in OMX Helsinki, OMX Stockholm and OMX Copenhagen and it is questionable whether these results can be generalized to concern other markets. Moreover, these results apply to the markets studied on average, so it may be the case that some of the patterns observed are market specific and hence more typical for some markets than for others. For example the overreaction observed by Mu et al. (2010) that does not seem to be observable in this study on average may be observable if one would study only one of these three markets. The fact that the news data is not perfect and contains some events that are not earnings announcement releases actually reinforces the findings of this study, since one can be fairly confident that most of the events in the sample are in reality releases of earnings announcements and a few others only add noise to the results.

9. CONCLUSIONS

The main goal of this study was to find out how the liquidity evolves around earnings announcements in limit order markets. This was conducted by studying 75 stocks traded in OMX Helsinki, OMX Stockholm and OMX Copenhagen around earnings announcements during four year sample period between 2006 and 2009. The other intention of this study was, based on the results concerning liquidity and earlier research, to address the question of how traders behave around earnings announcements and what happens to information asymmetries around earnings announcements.

The study found that during the 20 minute time window before the release of an earnings announcement the overall liquidity of the order book measured with β is stable but at rather low level. Also the mid-price stays stable during this window. This was interpreted so that not much trading takes place before the announcement, and, since the liquidity is at low level compared to normal times, it is likely that many traders have canceled their orders to avoid being picked-off after the release of the announcement. Additionally, based on earlier literature, the study proposes that the liquidity available before the announcement is mainly supplied by institutional investors and the ones who have canceled their orders are mainly individuals. However, somewhat in contrast to the behaviour of the liquidity measured with β, the study found that the spread is at rather normal level during the 20 minute time period before the announcement and and starts only slightly widen before the event.

The study found also that earnings announcements are followed by immediate negative liquidity shocks. Based on earlier research it is proposed that the shocks are caused by institutional investors triggering the stale limit orders of individual investors that have not been canceled before the announcement. This may indicate that the earnings announcement releases increase information asymmetries momentarily as institutional investors are able to quickly interpret the new information.

When comparing positive and negative announcements, the study found that while trades get executed on the other side of the book, the opposite side does not seem to stay unchanged and passive. This would indicate that both sides of the book react to the announcement. It was also observed that the reactions to the announcements were slightly slower in the case of negative events, but otherwise the return on mid-price evolved rather symmetrically around earnings announcements for positive and negative announcements.

20 minutes after the earnings announcement the overall liquidity of the limit order book measured with β seemed to have decreased to a normal level. This would indicate that all market participants have interpreted the new information and somewhat agree about the new price, and hence information asymmetries would have been reduced by the announcement when considering 20 minute time interval. However, the study found also that 20 minutes after the announcement the spread was still at higher level than normally. This suggests that 20 minutes after the earnings announcement the limit order book has not completely recovered from the liquidity shock caused by the release of the earnings announcement: the liquidity for large orders is at normal level but the liquidity for small trades taking place at the best quotas is at lower level than normally.

It remains for future research to find out more precisely which actions of traders are driving the liquidity effects observed in this study. Future research could also establish whether similar effects can be observed in other markets and if other measures of liquidity provide similar results. Also how much time it requires for the spread to recover would be an interesting topic beyond the scope of this study. One could also find out if there are differences between the markets included in this study. Further research could also be done to investigate if the financial crisis in 2008 had some impact on the behaviour of the order book around earnings announcements or liquidity in general. Especially interesting topic for future research would be to study what are the liquidity effects of non-scheduled corporate announcements that come as a surprise to the markets, since they are not expected and hence the reactions may be extremely different compared to the findings of this research.

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A. APPENDIX: COMPANIES

The following three tables, Table 4, Table 5 and Table 6 present the companies included in this study and how different types of earnings announcements are distributed between different companies. Column total news is the number of news in the data for the respective company between 1.1.2006-1.1.2010 and the next column, news with 27 previous days, includes the news in the total sample that have 27 previous days in the order book data, i.e. it is possible to form the required estimation window. News published 10:20-15:40 include the news that are additionally published during those hours and news in column no trading halts do not have any trading halts during the 40 minute time period around the release of the announcement. Liquid news are the ones that additionally have relatively liquid estimation windows, i.e. β during the 27 previous days does not exceed the threshold of 0.5, and they constitute the final sample studied. Positive news are the news of the final sample for which the mid-price has increased at the end of the estimation window compared to the value right before the release of the announcement and respectively the ones for which the mid-price has decreased are negative news. News for which the mid-price is unchanged are neutral news.

The numbers in column remarks have the following meanings:

1. was not in the index in 2009 but at the end of 2013
2. data from 3.7.2006 onwards
3. data from 10.10.2006 onwards
4. was in the index 2009 but no at the end of 2013
5. stock A was chosen because more traded than B
6. we study stock A which was in index 2009
7. we study stock B which was in index 2009

8. there are also announcements published under names Carlsberg Breweries A/S and Carlsberg Finans A/S, but in our announcement sample the announcements under name Carlsberg A/S were published first (before the same announcements under different names)

9. stock B was chosen because more traded than A

In addition, following companies that were in OMXH 25, OMXS 30 or OMXC 20 indexes at the end of 2013 or in 2009 but were excluded from the sample because there was no data available in the database for the company or the stock was not traded during the first year of the sample period (i.e. 2006):

- Talvivaara (OMXH)
- Nokia (OMXS)
- Pandora (OMXC)
- Chr. Hansen Holding (OMXC)
- DSV (OMXC)
- D/S Norden (OMXC)

Table 4: Stocks traded in Helsinki Exchange

name	remarks	total news	news with 27 previous days	news published 10:20-15:40	no trading halts	liquid news	positive news	negative news	neutral news
Nokia		15	14	12	11	11	8	3	0
TeliaSonera AB		14	14	0	0	0	0	0	0
UPM-Kymmene Oyj		14	13	8	8	8	5	3	0
Fortum		12	11	0	0	0	0	0	0
KONE Oyj		13	12	12	11	6	3	3	0
Amer Sports	1	16	16	15	15	4	1	3	0
Cargotec		14	13	10	9	5	3	2	0
Elisa		13	12	0	0	0	0	0	0
Huhtamäki Oyj	1	13	12	0	0	0	0	0	0
Konecranes Oyj		14	14	0	0	0	0	0	0
Kesko Oyj		14	13	0	0	0	0	0	0
Kemira Oyj	1	14	13	1	1	1	0	1	0
Metso Oyj		15	14	14	13	10	4	6	0
Nordea Bank AB (publ.)		11	11	1	1	1	1	0	0
Neste Oil Oyj		14	14	0	0	0	0	0	0
Nokian Renkaat		14	14	1	1	1	1	0	0
Orion	2	12	11	7	7	3	1	2	0
Outotec Oyj	3	9	9	0	0	0	0	0	0
Pohjola Pankki Oyj		14	14	0	0	0	0	0	0
Rautaruukki		14	13	2	2	2	1	1	0
Sampo		14	14	0	0	0	0	0	0
Stora Enso Oyj		16	15	7	6	6	3	3	0
Wärtsilä		13	12	0	0	0	0	0	0
YIT		13	13	0	0	0	0	0	0
Outokumpu Oyj		15	14	10	9	6	1	5	0
Sanoma Oyj	4	14	13	1	1	0	0	0	0
Tieto		19	18	2	2	1	0	1	0
27	sum:	373	356	103	97	65	32	33	0

Table 5: Stocks traded in Stockholm Exchange

name	remarks	total news	news with 27 previous days	news published 10:20-15:40	no trading halts	liquid news	positive news	negative news	neutral news
ABB Ltd		8	8	0	0	0	0	0	0
Alfa Laval AB		12	12	6	6	6	4	2	0
ASSA ABLOY AB		16	16	5	5	5	2	2	1
Atlas Copco AB	5	15	13	10	9	9	5	3	1
AstraZeneca PLC		12	12	11	11	11	6	5	0
Boliden AB		13	12	9	7	7	4	3	0
Electrolux, AB		13	13	1	1	1	0	1	0
Ericsson, Telefonab. L M		30	30	1	1	1	0	1	0
Getinge AB		11	11	6	6	6	4	2	0
Hennes & Mauritz AB, H & M		11	11	0	0	0	0	0	0
Investor AB		11	11	0	0	0	0	0	0
Lundin Petroleum AB		10	10	0	0	0	0	0	0
Modern Times Group MTG AB		12	12	9	9	9	7	2	0
Nordea Bank AB (publ)		13	13	1	1	1	0	0	1
Sandvik AB		14	13	5	5	5	1	3	1
Svenska Cellulosa AB SCA		12	12	5	4	1	1	0	0
SCANIA AB		14	14	7	7	6	4	2	0
Skandinaviska Enskilda Banken AB		16	16	5	5	5	3	1	1
Securitas AB		8	8	1	1	1	0	0	1
Skanska AB		13	13	7	7	1	0	0	1
SKF, AB		13	13	1	1	5	3	1	1
SSAB AB		10	10	5	5	5	2	3	0
Swedbank AB		12	12	5	5	6	3	2	1
Swedish Match AB		13	13	6	6	1	1	0	0
Tele2 AB		12	12	1	1	0	0	0	0
TeliaSonera AB		13	13	0	0	0	0	0	0
Volvo, AB		14	14	0	0	0	0	0	0
Svenska Handelsbanken AB	6	12	12	0	0	7	2	3	2
28	sum:	363	359	107	103	99	52	36	11

Table 6: Stocks traded in Copenhagen Exchange

name	remarks	total news	news with 27 previous days	news published 10:20-15:40	no trading halts	liquid news	positive news	negative news	neutral news
Novo Nordisk A/S		11	11	0	0	0	0	0	0
Novozymes A/S		12	12	4	0	0	0	0	0
TDC A/S	1	12	12	0	0	0	0	0	0
Topdanmark A/S		11	11	11	7	6	4	2	0
Tryg A/S		13	13	1	1	1	0	1	0
Vestas Wind Systems A/S		12	12	0	0	0	0	0	0
William Demant Holding A/S		9	9	3	1	1	0	1	0
Carlsberg A/S	7,8	12	12	0	0	0	0	0	0
Coloplast A/S		12	12	7	4	4	2	2	0
Danske Bank A/S		12	12	6	2	2	1	1	0
FLSmidth & Co. A/S		12	12	11	7	6	4	2	0
Genmab A/S		12	12	0	0	0	0	0	0
GN Store Nord A/S	1	11	11	9	6	5	1	4	0
Jyske Bank A/S	1	13	13	6	3	2	1	1	0
A.P. Mller - Mrsk A/S	9	8	8	4	3	3	1	2	0
Nordea Bank AB		15	15	1	1	1	0	0	1
H. Lundbeck A/S	4	12	12	0	0	0	0	0	0
Danisco A/S	4	12	12	11	7	6	6	0	0
NKT Holding A/S	4	12	12	6	5	4	2	2	0
Sydbank A/S	4	12	12	12	8	6	1	5	0
20	sum:	235	235	92	55	47	23	23	1

B. APPENDIX: RESULTS OF PEARSON'S χ^2 TEST

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
H0_a * event	422	100,0%	0	0,0%	422	100,0%

H0_a * event Crosstabulation

			event		Total
			0	1	
H0_a	0	Count	163	19	182
		% within event	77,3%	9,0%	43,1%
	1	Count	48	192	240
		% within event	22,7%	91,0%	56,9%
Total		Count	211	211	422
		% within event	100,0%	100,0%	100,0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	200,334[a]	1	,000		
Continuity Correction[b]	197,561	1	,000		
Likelihood Ratio	223,016	1	,000		
Fisher's Exact Test				,000	,000
Linear-by-Linear Association	199,859	1	,000		
N of Valid Cases	422				

a. 0 cells (0,0%) have expected count less than 5. The minimum expected count is 91,00.

b. Computed only for a 2x2 table

Figure 23: Results of Pearson's χ^2 test for absolute changes in β on the ask side. H0_a gets value 1 if the hypothesis H_0 gets rejected meaning that the distribution of the changes in the event window is not the same as in the estimation window, otherwise it gets the value of 0. Variable event gets the value of 1 if there was an event in the event window and 0 if it was a random moment. The first line of the bottom table gives the results of the Pearson's χ^2 test: row Value gives the value of the χ^2 test statistic, row df gives the degrees of freedom and row Asymp. Sig. (2-sided) gives the p-value. The results and tables are obtained by using SPSS.

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
H0_b * event	422	100,0%	0	0,0%	422	100,0%

H0_b * event Crosstabulation

			event		Total
			0	1	
H0_b	0	Count	147	22	169
		% within event	69,7%	10,4%	40,0%
	1	Count	64	189	253
		% within event	30,3%	89,6%	60,0%
Total		Count	211	211	422
		% within event	100,0%	100,0%	100,0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	154,215[a]	1	,000		
Continuity Correction[b]	151,757	1	,000		
Likelihood Ratio	168,126	1	,000		
Fisher's Exact Test				,000	,000
Linear-by-Linear Association	153,849	1	,000		
N of Valid Cases	422				

a. 0 cells (0,0%) have expected count less than 5. The minimum expected count is 84,50.

b. Computed only for a 2x2 table

Figure 24: Results of Pearson's χ^2 test for absolute changes in β on the bid side. H0_b gets value 1 if the hypothesis H_0 gets rejected meaning that the distribution of the changes in the event window is not the same as in the estimation window, otherwise it gets the value of 0. Variable event gets the value of 1 if there was an event in the event window and 0 if it was a random moment. The first line of the bottom table gives the results of the Pearson's χ^2 test: row Value gives the value of the χ^2 test statistic, row df gives the degrees of freedom and row Asymp. Sig. (2-sided) gives the p-value. The results and tables are obtained by using SPSS.

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
H0_lna * event	422	100,0%	0	0,0%	422	100,0%

H0_lna * event Crosstabulation

			event		
			0	1	Total
H0_lna	0	Count	169	21	190
		% within event	80,1%	10,0%	45,0%
	1	Count	42	190	232
		% within event	19,9%	90,0%	55,0%
Total		Count	211	211	422
		% within event	100,0%	100,0%	100,0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	209,698[a]	1	,000		
Continuity Correction[b]	206,874	1	,000		
Likelihood Ratio	233,470	1	,000		
Fisher's Exact Test				,000	,000
Linear-by-Linear Association	209,201	1	,000		
N of Valid Cases	422				

a. 0 cells (0,0%) have expected count less than 5. The minimum expected count is 95,00.

b. Computed only for a 2x2 table

Figure 25: Results of Pearson's χ^2 test for relative changes in β on the ask side. H0_lna gets value 1 if the hypothesis H_0 gets rejected meaning that the distribution of the changes in the event window is not the same as in the estimation window, otherwise it gets the value of 0. Variable event gets the value of 1 if there was an event in the event window and 0 if it was a random moment. The first line of the bottom table gives the results of the Pearson's χ^2 test: row Value gives the value of the χ^2 test statistic, row df gives the degrees of freedom and row Asymp. Sig. (2-sided) gives the p-value. The results and tables are obtained by using SPSS.

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
H0_lnb * event	422	100,0%	0	0,0%	422	100,0%

H0_lnb * event Crosstabulation

			event		Total
			0	1	
H0_lnb	0	Count	160	29	189
		% within event	75,8%	13,7%	44,8%
	1	Count	51	182	233
		% within event	24,2%	86,3%	55,2%
Total		Count	211	211	422
		% within event	100,0%	100,0%	100,0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	164,451[a]	1	,000		
Continuity Correction[b]	161,950	1	,000		
Likelihood Ratio	178,115	1	,000		
Fisher's Exact Test				,000	,000
Linear-by-Linear Association	164,062	1	,000		
N of Valid Cases	422				

a. 0 cells (0,0%) have expected count less than 5. The minimum expected count is 94,50.

b. Computed only for a 2x2 table

Figure 26: Results of Pearson's χ^2 test for relative changes in β on the bid side. H0_lnb gets value 1 if the hypothesis H_0 gets rejected meaning that the distribution of the changes in the event window is not the same as in the estimation window, otherwise it gets the value of 0. Variable event gets the value of 1 if there was an event in the event window and 0 if it was a random moment. The first line of the bottom table gives the results of the Pearson's χ^2 test: row Value gives the value of the χ^2 test statistic, row df gives the degrees of freedom and row Asymp. Sig. (2-sided) gives the p-value. The results and tables are obtained by using SPSS.

C. APPENDIX: AR-MODEL

AR(1) refers to first-order autoregressive process. In general the model can be written as

$$x_t - \phi x_{t-1} = a_t,$$

where x_t and x_{t-1} are successive observations, ϕ is a coefficient and a_ts for different values of t are uncorrelated variables from a fixed distribution, often referred as white-noise. (Mills 1991) In our case the model for changes in β can be written as

$$\Delta\beta_t - \phi\Delta\beta_{t-1} = e_t$$

and accordingly also for the changes in $\ln(\beta)$. One could say about the AR(1)-model that we estimate that $\Delta\beta$ at a specific moment t is $\Delta\beta$ of the previous moment $t-1$ and the error of our estimate is e_t. In this study what actually is being studied are these white-noise terms e_ts which should not be autocorrelated. So in the end if we observe abnormally large values for e_t around news events we can say that the behavior of the book has not been normal. After fitting the AR(1)-model we consider the residuals to be i.i.d., but we do not test this on the whole sample due to computational intensiveness.

D. APPENDIX: STANDARD DEVIATION OF β AROUND EARNINGS ANNOUNCEMENTS

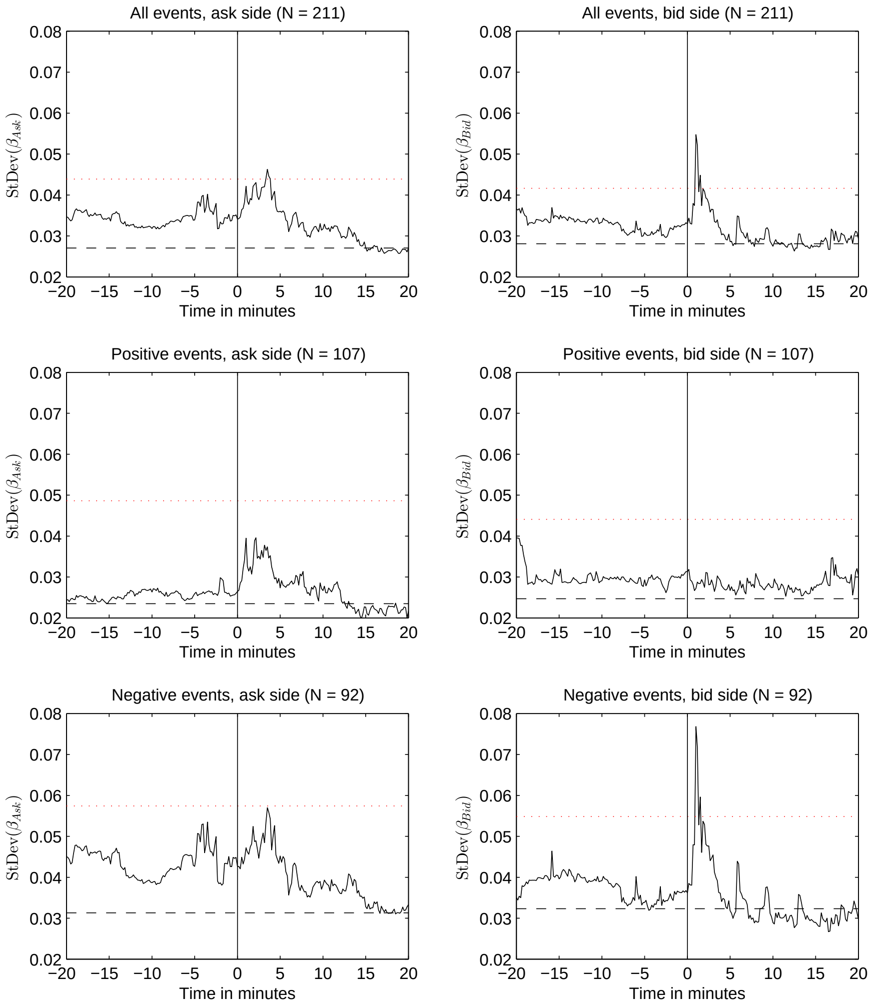

Figure 27: Standard deviation of β around earnings announcements for all events, positive events and negative events. Black solid line corresponds to StDev(β), black dashed line corresponds to the average of StDev(β) in the estimation window and red dotted line corresponds to the maximum value of StDev(β) in the estimation window. The black line at time zero corresponds to the time of the earnings announcement.